INVESTIGATING THE EFFECT OF UTILIZING LEARNING ANALYTICS ON STEM TEACHERS' EFFICACY, RESILIENCY, AND DATA ANALYTICS KNOWLEDGE

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ABSTRACT

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High novice teacher turnover rate and shortage of skilled novice teachers continue to be an unsolved issue in the U.S. educational system. Novice teachers often suffer low teaching efficacy which may reduce their teacher resiliency and lead to teacher turnover. Past studies suggested that novice teachers' low teaching efficacy results from their scant teaching experience and their inability to assess impacts of their teaching on students. The failure for novice teachers to utilize effective pedagogies and improve student learning often results in elevated professional anxiety, frustration, and motivation to quit teaching. Recent studies pointed out that learning analytics could help novice teachers to teach more effectively by tapping into student data and data analytics. But how to structure a professional development for novice teachers to learn to utilize learning analytics in teaching remains a question. To address these issues, a survey study and a case study are conducted in this research. The survey study analyzed 72 teachers' perceptions and experience of using learning analytics in teaching. The results indicated common barriers for teachers to use learning analytics such as lack of awareness of learning analytics, insufficient computer skills and math/statistics knowledge. Also, when

teachers considered learning analytics useful, their usage of learning analytics correlated positively with teaching efficacy and teacher resiliency. Built upon insights from the survey study, the case study recruited five novice teachers and investigated the effects of a learning analytics professional development.

The results suggested that after the learning analytics professional development, all participants have generally improved their learning analytics knowledge, teaching efficacy, teacher resiliency, and developed higher confidence and intention to use learning analytics in future teaching. One implication of these results is that using teaching scenario could be an effective format to structure learning analytics professional development to improve novice teachers' competence in assessing teaching practices and their teaching efficacy. Another implication is that learning analytics professional development could be implemented as intervention in teacher education programs to reduce the likelihood of teacher turnover before novice teachers start teaching formally.

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TABLE OF CONTENTS

APPENDICES

LIST OF TABLES

Table

LIST OF FIGURES

Figure

Table

Chapter I

INTRODUCTION

> Our inability to support high-quality teaching in many of our schools is driven not by too few teachers coming in, but by too many going out. We need to balance our efforts to prepare high-quality teachers with strong strategies to support good teaching in our schools. (Tom Carroll, National Commission on Teaching & America's Future [NCTAF] Report, 2003)

There is continuing high demand for skilled teachers in the Science, Technology, Engineer, Mathematics (STEM) subject areas, but the chronic shortage of qualified STEM teachers has continued to grow as an unresolved issue in the U.S. educational system. One reason for this shortage may have to do with the low enrollment in STEM teacher education programs. STEM majors are often attracted by more lucrative rewards in job areas other than education. Comparing the 2010 to 2016 school year, total enrollment in teacher education programs nationwide has decreased by more than one-third. This suggests a decrease of 340,000 people who could potentially become teachers during that interval. Even after students have successfully enrolled into a teacher education program, there is the issue of decreased completion rate. For students who have joined a STEM teacher education program, a 22% decline was seen between 2012 and 2018 in the number of students who completed their program and began teaching in a STEM subject area (Partelow, 2019). The number of new STEM teachers entering the public-school system is declining, and there is an estimate that U.S. schools will be short by 200,000 new teachers every year. By 2025, that number is expected to increase to 316,000 annually (Sutcher, Darling-Hammond, & Carver-Thomas, 2016). This shortage of teachers is seen across all STEM subject areas. For example, in 2019, there were about 30,000 vacancies for physics teachers nationwide, but only 6,000 students majoring in physics education.

Statement of the Problem

Even after teachers enter the school system, this teacher shortage continues to grow, as high teacher turnover rates are seen within the first few years. Of the 9,200 new teachers entering the school system, more than 39% are likely to leave their jobs within the first 5 years of teaching (Ingersoll, 2000). This high turnover rate is seen more frequently among STEM subject teachers. Such loss has cost the U.S. about $7 billion per year (Sutcher et al., 2016). Marder, Plisch, and Brown (2017) described this as one of the largest challenges that U.S. public schools are facing, and that teacher shortage is one of the predominant reasons to explain U.S. students' low performance on STEM subjects as seen in international assessments such as PISA and TIMSS (Organisation for Economic Co-operation and Development [OECD], 2016).

More recently, studies have pointed to the gap between theory and practice in current teacher education curricula. Loughran (2014) found that many preservice teachers' teaching skills are not applicable due to their lack of teaching experience. This may be due to many teacher training programs shortening their teacher training curricula and graduating students early to make up for the high demand for new teachers. As a result, student teachers are left with limited experience before they start teaching full-time (Sutcher et al., 2016).

Limited teacher training and experience have not only led to the lack of teaching competency but also to the lack of teaching efficacy for novice teachers. Research has suggested that this lack of teaching efficacy may have triggered elevated stress, disappointment in work performance, and occupational fatigue in novice teachers, leading to high teacher turnover rate (Gu & Day, 2013). A plethora of studies has suggested that building teaching efficacy can lead to higher teacher resiliency (Coladarci, 1992; Evans & Tribble, 1986; Gibson & Dembo, 1984). Studies have found that resilient teachers often have high self-efficacy in teaching (Gu & Day, 2013). Teaching efficacy has been described as “a little idea with big impact” on teacher resiliency, and an especially important ability for novice teachers to develop as they begin their teaching career (Kitching, 2009; Tait, 2008; Tschannen-Moran & Hoy, 2007). These studies have revealed that for both preservice and in-service teachers, having high teaching efficacy can increase their commitment to teaching and possibly reduce teacher turnover.

Many studies have focused on utilizing different formats of professional development to enhance teachers’ pedagogical competence (Colbert, Brown, Choi, & Thomas, 2008; Donna, 2013; Grigg, Kelly, Gamoran, & Borman, 2012; Heller, Daehler, Wong, Shinohara, & Miratrix, 2012), but these studies have focused heavily on in-service teachers but not preservice or novice teachers. While these research findings are informative in terms of their approaches to increase in-service teachers’ teaching skills, Ingersoll (2000) pointed out that experienced teachers tend to be concerned about their relationship with the parents and school leadership, while novice teachers are more concerned about their teaching skills and worry mostly about how their teaching affects students' learning outcomes. This implies that the needs of novice teachers may differ greatly from experienced teachers.

One reason for low teaching efficacy for novice teachers may have to do with the lack of skill and training for novice teachers to assess their own teaching skills and their students' learning progressions (Morine-Dershimer & Kent, 1999). Firestone (2014) argued that our current teaching evaluation for novice teachers has continued to focus on metrics that mainly explain their levels of performance, but not provide them with useful feedback for pedagogical improvement. Recently, growing evidence has shown that using learning analytics can help teachers improve their teaching practices and enhance students' learning outcomes (Armstrong & Anthes, 2001). Major findings in this research area indicated that utilizing data analytics tools and students' learning data can help novice teachers receive more informative feedback to help them teach more effectively (Dawson, McWilliam, & Tan, 2008). However, despite these study findings, little research has been conducted on how learning analytics may play a role in increasing novice teachers' teaching efficacy and teacher resiliency.

Moving forward, "teachers" refers to teachers in the STEM subject areas, and "novice teachers" refers to preservice and teachers with less than 5 years of teaching experience.

Purpose of the Study

High teacher turnover rate is a serious problem in U.S. public education. Novice teachers, who have little teaching experience, tend to lack skills and training when it comes to assessing their own teaching and their students' learning performance. Oftentimes, this may lead to novice teachers having low teaching efficacy and teacher resiliency (Gibson & Dembo, 1984). This dissertation research examined if learning analytics professional development can assist teachers in developing skills to assess their own teaching practices and student performance, and how such skills may influence their teaching efficacy and teacher resiliency. The main purpose of this research was to see if learning analytics can serve as an effective intervention to make novice teachers more professionally resilient.

Research Questions

1. What are the challenges, perspectives, and usage patterns of learning analytics in STEM teachers/educators, and how does that influence their teaching efficacy?
2. Can learning analytics professional development assist teachers in developing skills to assess their own teaching practices and student performance, and how does such skills and training influence their teaching efficacy and teacher resiliency?

To answer these two research questions, I conducted a learning analytics survey study and a case study for this dissertation. The learning analytics survey study explored the first research question to identify the challenges, perspectives, and usage patterns of learning analytics for STEM teachers. The findings were used to inform the intervention design for the case study which explored the second research question.

This dissertation is organized in the following sequence. First, I provide a literature review that leads to the two research questions. Then, I elaborate on the details and results of the learning analytics survey study to answer the first research question. Afterwards, I explain the details of the case study and its findings to answer the second question. This dissertation concludes with a general discussion, research limitation, implications, and suggestions for future research.

Chapter II

LITERATURE REVIEW

In this chapter, I first give an overview on the current high teacher turnover rate and how it relates to our teacher education system. The next section takes a closer look on how the needs of novice teachers may differ from experienced teachers, exploring the challenges novice teachers have in accurately assessing their teaching and their students' learning outcomes. Later, this review considers how professional development may help address these issues to increase novice teachers' teaching efficacy and teacher resiliency. Finally, I discuss the use of learning analytics in professional development and address the applicable format to conduct this type of professional development for novice teachers.

High Teacher Turnover Rates and Teacher Shortage

Several contextual and individual factors could contribute to high teacher turnover. In this section, I review relevant literature and explain why more research attention should be paid to novice teachers instead of school administration/leadership in order to address high teacher turnover and teacher shortage.

Past literature has pointed out that some contextual risk factors affect teachers' teaching commitment and job retention. Boyd, Grossman, Lankford, Loeb, and Wyckoff

(2005) found that school location could affect teacher retention. Teachers who taught at schools located in high-poverty urban areas tended to leave their teaching sooner than other teachers. School location also seems to connect with educational resources and investments, which is another factor that influences teacher turnover. Darling-Hammond and Carver-Thomas (2017) found that teachers in the southern states exhibited higher turnover rates than those in the northern states. This difference was due to a smaller class size and a higher number of investments in educational resources in northeastern states. These advantages in northeastern states led to less workload, better pedagogical support, and a higher retention rate for teachers in those regions.

Student demographics and backgrounds are also associated with teacher turnover. Howard and Johnson (2004) conducted a study on novice teachers who taught a high portion of disadvantageous students in their class. Common challenges these teachers encountered included disobedient or violent student behaviors in class on a daily basis. Howard and Johnson suggested a positive correlation between these teachers' experiences of coping with these disadvantageous students and their motivation to quit teaching.

Support from colleagues and school leadership also matters in terms of teacher retention. When novice teachers perceived they could acquire assistance from school leadership through professional development and colleague mentoring, they showed a higher tendency to stay in teaching (Jenkins, Smith, & Maxwell, 2009; Simon & Johnson, 2015). In contrast, Anderson and Olsen (2006) and Yost (2006) found that poor collegial relationships, lack of teaching resources, and heavy workload contributed largely to novice teachers' burnout and turnover.

Although past studies have shown that contextual risk factors exerted some influences on teacher turnover which inevitably led to teacher shortage, it is worth noting that these contextual risk factors and potential remedies were out of novice teachers' control. For instance, novice teachers may not be able to decide in which school (s)he will teach or improve the quality of school leadership. In this dissertation research, instead of centering on specific educational policy or specific type of organizational leadership, I focused on intervention at the individual level to address novice teachers' needs which particularly led to their high turnover rate in their earlier teaching careers.

Challenges in Teaching Practices Among Preservice and Novice Teachers in Comparison to Experienced Teachers

Past studies have suggested that there are some similarities and differences in terms of the challenges that novice and experienced teachers need to face. The common challenges include heavy administrative workload and classroom management (Ingersoll, 2002). However, the needs of novice teachers may differ largely from the experienced teachers in terms of pedagogical practices. Ulvik and Langørgen (2012) conducted a field research to study different teachers' practices between 80 novice teachers and 40 experienced teachers. The results suggested that experienced teachers tended to encounter challenges such as utilizing up-to-date information and communication technologies (ICT) to facilitate students' learning or being overly customized to school culture and not be able to examine their pedagogical strategies critically. For novice teachers, the challenges were related mostly to lack of confidence in their teaching skills and their pedagogical influence on student learning. The challenge for novice teachers to develop effective teaching practices can be larger when students have special needs.

Fantilli and McDougall (2009) pointed out that novice teachers often had difficulties creating instruction for exceptional students or students who required special education due to their lack of teaching experience. Novice teachers often feel insecure and inexperienced, and lack preparation for teaching (Beltman, Mansfield, & Price, 2011). To address novice teachers' insufficient teaching experience and teaching skills, some researchers have directed their attention to creating additional assistance for novice teachers once they start teaching.

Hogan, Rabinowitz, and Craven (2003) contended that support from school leadership and school districts to provide subject-specific professional development for novice teachers could help novice teachers transition from their teacher education programs to formal school teaching. Fantilli and McDougall (2009) emphasized that the timeframe to onboard a novice teacher is oftentimes short and not enough for a novice teacher to become familiar with the school culture and teaching curriculum. Novice teachers' perception of underpreparedness for teaching could easily overwhelm them, and this issue could be ameliorated by changing the hiring process (p. 824). These findings about additional assistance which novice teachers may need are constructive. But it is worth noting that the timing of remedial strategies is after novice teachers have begun their teaching careers, and their overwhelming workload, mental burden, work stress, and challenge to balance their personal and professional life may reduce the effectiveness of these supports (Beltman et al., 2011). A more productive approach to address novice teachers' lack of teaching experience and teaching skills may be examining issues underlying their teaching practice in their teaching education programs.

There are two major issues regarding teaching practice for novice teachers. The first major issue is that novice teachers often lack constructive feedback on their teaching. Teaching practice for most novice teachers often involves a structured teaching internship or practicum, where novice teachers are given the opportunity to practice teaching during their teacher education programs (Dieker, Hughes, Hynes, & Straub, 2017). Novice teachers are usually assessed by other senior teachers or mentors which will determine their qualification to become formal teachers. Firestone (2014) suggested that most of the current teacher education programs in the United States place an excessive emphasis on different metrics to evaluate preservice teachers' teaching performance, but do not give useful feedback for them to examine their pedagogical impact on students. The second major issue about teaching practice novice teachers is that novice teachers might not know how to evaluate the effects of their instructional approach on students. Novice teachers' inability to assess their own teaching may lead them to repeat less effective pedagogies unconsciously (Roberson & Roberson, 2009), or fail to adjust the pace or depth of their teaching practices for different students (Dieker et al., 2017). The ability to utilize information and feedback to improve teaching is crucial not only to students' learning outcomes, but also to novice teachers' well-being and motivation to teach. Jamil, Downer, and Pianta (2012) conducted a survey to examine 509 preservice teachers' performance, well-being, and teachers' self-efficacy at the beginning of the teaching practicum and at the end of their teacher education programs. The results showed that novice teachers' perceptions of their failure to improve their teaching and using ineffective pedagogies repeatedly were major contributors to novice teachers' frustration, dissatisfaction, low teaching efficacy, and program incompletion.

Importance of Teaching Efficacy, Teacher Resiliency, and Professional Development

Teaching efficacy is important to make novice teachers more resilient in their teaching careers (Tschannen-Moran & Hoy, 2007). In this section, I review past studies on how professional development can increase novice teachers' teaching efficacy and teacher resiliency. I first describe the concept of teaching efficacy and explain its connection with teacher resiliency. I also discuss how to utilize professional development as an approach to potentially enhance novice teachers' teaching efficacy and resiliency, and how it can possibly reduce teacher turnover.

Bandura (1993) described self-efficacy as a personal judgment of how well one can execute courses of action required to deal with prospective situations. According to Bandura, there are several different ways for individuals to gain self-efficacy, such as mastery experience of a task, positive psychological feedback, social persuasion (e.g., encouragement), and vicarious experience by modeling others' successful behaviors. The concept of teaching efficacy was derived from self-efficacy. Teaching efficacy is defined as a teacher's belief that one is able to complete various activities, including structuring and implementing lesson plans, responding to students' needs during their learning task, managing the classroom, and applying various teaching practices to improve students' learning outcomes (Bandura, 1997; Tschannen-Moran & Hoy, 1998). Teaching efficacy is not a direct measure of one's competence; instead, it is a measure of a teacher's confidence in a projected teaching circumstance within a given context (Hoy, 2000).

Resilience was described as positive emotions, such as joy, interest, contentment, and love, which could become individuals' physical and intellectual resources to increase the odds of successful coping and survival (Fredrickson & Neill, 2004, p. 1367). Teacher resiliency is defined as teachers' ability to persist in challenging teaching scenarios and cope with stress for teachers (Beltman et al., 2011). Teacher resiliency can also be seen as a psychological property. Gu and Day (2007) suggested teacher resiliency as teachers' emotional intelligence to maintain commitment and effectiveness in teaching in the face of adversity in teachers' professional work and personal life. Teacher resiliency has been considered key for novice teachers' thriving (Tait, 2008).

There is a plethora of empirical evidence for the positive connection between teaching efficacy and teacher resiliency. Many studies have found teachers with higher teaching efficacy tended to be more resilient in terms of coping with work stress and anxiety, avoiding professional burnout (Kitching, 2009; Tait, 2008; Tschannen-Moran & Hoy, 2007), and increasing longevity for their teaching careers (Gibson & Dembo, 1984). The first few years of teaching experience matter a lot to novice teachers' retention in teaching. Burley, Hall, Villeme, and Brockmeier (1991) concluded that novice teachers with higher teaching efficacy also had a higher tendency to stay in teaching after they started their first teaching jobs. For novice teachers who quit their jobs in the early years of teaching, it was found that they had lower teaching efficacy and decided to stay in teaching (Glickman & Tamashiro, 1982). Tschannen-Moran and Hoy (2001) did an extensive review of past measures that attempted to capture the construct of teaching efficacy. Through repetitive and rigorous tests with different preservice and in-service teacher populations, Tschannen-Moran and Hoy established a reliable teaching efficacy measure that has been widely used by other researchers who were interested in the same topic. Tschannen-Moran and Hoy also validated that teaching efficacy is the key to teachers' persistence, enthusiasm, commitment, and student achievement.

The connection between teaching efficacy and teacher resiliency has encouraged many researchers to focus on using professional development to enhance teaching efficacy and increase teacher resiliency for novice teachers. Those past studies focused on the connection between teachers' technological pedagogical content knowledge (TPACK) and teaching efficacy. TPACK is defined as teachers' knowledge of using various technologies, pedagogical designs in different teaching settings, and their deep understanding of the subjects they teach in order to enhance students' learning outcomes (Schmidt et al., 2009). TPACK could be measured by different sub-measures such as PK (pedagogical knowledge) and TPK (technological pedagogical knowledge) developed by Schmidt et al. Other studies have adopted the original TPACK measure with research focus on professional development. For example, Banas and York (2014) modified the original PK and TPK measures by removing questions about teachers' perceptions of their teacher education program and classroom management ability to focus on effects of the professional development in their study. Banas and York's measures were also adopted by Byker, Putman, Handler, and Polly's (2017) study of 63 elementary school preservice teachers' intention to integrate technologies to engage students in social studies. Their results suggested that in order to help teachers successfully use educational technologies in teaching, it is important that teachers have examples, guidance, and time to develop a comprehensive teaching plan to use technologies in their own teaching. Byker et al.'s results also suggested that teachers' TPK and intentions to utilize technologies in teaching correlated positively with their teaching efficacy.

The connection between teachers' TPACK, teaching efficacy, and teacher resiliency has spurred many researchers to focus on different formats of professional development. For instance, Colbert et al. (2008) found that using a teacher-driven professional development in which teachers could decide the format and process of professional development was more helpful to increase their teaching skills than lecturer-led seminars. Grigg et al. (2012) suggested that using case study in professional development, where teachers can imagine themselves in an actual challenging situation, could help them put their teaching theories into practice to create more student-centered instructions. Other professional development formats such as engineering-oriented (Donna, 2013) and scientific inquiry-based approaches (Heller et al., 2012) have also shown the potential to enhance teachers' TPACK and teaching efficacy.

Despite these fruitful research findings, these professional development studies focused on in-service teachers but not preservice or novice teachers (O'Brien & Jones, 2014). Although TPACK is imperative to teachers' pedagogical performance (Harris & Hofer, 2011), novice teachers are concerned about "if they are able to teach" rather than "which ways they should use to teach" (Fimian & Blanton, 1987; Ingersoll, 2000). Hong (2012) conducted an in-depth study to analyze a group of 14 novice teachers who had less than 5 years of teaching experience. The author compared the novice teachers who left their teaching jobs with those who stayed in teaching after they completed their teacher education program. The results showed that one of the major factors that affected novice teachers' leave/stay choice was if they received any kind of professional development which focused on strengthening their confidence and ability to teach. Hong concluded that professional development which focused on novice teachers' teaching efficacy is the key to teacher resiliency. This type of professional development should have training content that focuses on teaching practice, self-assessment, and reflection for novice teachers to strengthen their teaching efficacy (Morine-Dershimer & Kent, 1999).

The Use of Learning Analytics and Educational Data Mining for Pedagogical Improvement

In this section, I discuss how learning analytics and educational data mining have become popular research subjects to improve teachers' teaching practices. I first distinguish learning analytics from educational data mining and then discuss past studies that focused on using learning analytics to enhance teaching and learning outcomes.

Educational data mining develops and adopts statistical, machine-learning, and data-mining methods to study educational data generated basically by students and instructors. Their application may help to analyze student learning processes, considering their interaction with the environment (Liñán & Pérez, 2015, p. 100). Learning analytics is defined as the measurement, collection, analysis, and reporting of data about learners and their contexts for the purposes of understanding and optimizing learning and the environments in which they occur (p. 103). The similarities between educational data mining and learning analytics are that both areas of research focus on using data to extract useful insights in order to enhance teaching and learning outcomes for teachers and students. The difference is that educational data mining focuses on educational software, automating data analysis, and modeling, while learning analytics centers on empowering students and instructors, use of human judgment, and design of interventions to enhance educational outcomes (Liñán & Pérez, 2015).

There have been many successful applications of educational data mining. Hübscher and Puntambekar (2008) applied data mining techniques to extract information from a web-based educational system to provide insights for pedagogical scaffolding. Based on data insights, students can receive different prompts in the same learning systems to solve physics questions more easily. Slater et al. (2016) used data mining to map semantic features and correlations between mathematical questions created by teachers' and students' responses in a learning system. Slater et al. discovered correlations between certain question semantics with students' learning engagement reflected by response semantics such as boredom, frustration, and confusion. These semantic discoveries could be used for pedagogical design in an online learning environment.

Although there have been many successful cases of using educational data mining for pedagogical design, this dissertation focused on the teachers' use of learning analytics to improve their teaching. Pedagogical design and improvement rely heavily on teachers' subject and pedagogical knowledge. Compared to educational data mining, learning analytics highlights instructors' role in discovering, analyzing, and utilizing educational data insights. Learning analytics also emphasizes a systematic view of educational data and intervention design to improve learning. In that regard, learning analytics fits into the scope of this dissertation research, with its focus on professional development for teachers, teaching efficacy, and teacher resiliency. In the following, I review past studies that applied learning analytics for pedagogical improvement.

Data-driven approaches have been proven to improve curriculum design effectively by teaching design. As more and more school districts and teachers are adopting data analytics into their professional development, an increasing body of evidence indicates that using learning analytics in instructional strategies can increase students' achievement (Armstrong & Anthes, 2001). Large volumes of student learning data are stored in learning management systems (LMSs), which school administrators and teachers can use to make good administrative and pedagogical decisions. For instance, Campbell, DeBlois, and Oblinger (2007) have used massive course management system data at a university to capture important factors of at-risk students in order to implement early learning interventions. Morris (2004) analyzed data from 354 students from several asynchronous online classes and identified student characteristics that could increase students' persistence in course activities. Morris used these students' characteristics for a learning intervention design and successfully improved students' academic performance. Student interaction is an important social element for students' learning outcomes. To overcome the shortcoming of online courses which often lack in-person interaction, Poon, Kong, Yau, Wong, and Ling (2017) used data visualization to investigate students' online participation, while Dawson et al. (2008) used online discussion forum data to increase students' interaction. Both studies identified the benefits of using various types of data to improve students' engagement and learning outcomes in the online learning environment.

Learning analytics can potentially increase teachers' TPK, teaching efficacy, and teacher resiliency, especially for novice teachers who lack teaching experience and skills to assess their teaching. The key to unlocking the pedagogical values of student data is teachers' learning analytics knowledge and skills (Dawson et al., 2008). As learning analytics is not part of the regular curricula for teacher education programs, an ideal alternative could be a learning analytics professional development catered specifically for novice teachers.

Suggested Approach to Professional Development in Learning Analytics with Novice Teachers

Although many past studies have suggested the promise of using learning analytics to enhance novice teachers' teaching efficacy, very little research has illuminated which format of professional development would be appropriate to teach novice teachers to use learning analytics in teaching. Different professional development formats may have different advantages and disadvantages in terms of teacher training. Some of the most common formats of professional development for teachers included workshop, class observation, and case study. Villegas-Reimers (2003) published a booklet with UNESCO's International Institute of Educational Planning that focused on an international literature review of teachers' professional development. In that booklet, the author elaborated how different formats of professional development have been applied to attain various teachers' training purposes along with their pros and cons. Villegas-Reimers described that workshops, seminars, and course lectures were the most common and traditional format of professional development for in-service teachers. These formats of professional development shared the nature of direct teaching. Also, this type of direct teaching professional development was relatively convenient to organize. However, the drawbacks of this type of direct-teaching professional development are that they are oftentimes "one-shot" knowledge delivery and their content might not be related to teachers' actual needs. Studies have shown that this type of one-shot and direct-teaching professional development can be more effective if teachers could join the decision-making process to decide the topics for their own professional development workshop or course lectures (Colbert et al., 2008).

Another widely used format of professional development is case-based learning. Case-based learning in professional development focuses on real-world teaching scenarios that engage teachers in building their ability to unravel complex, ambiguous, and conflicting teaching problems without best answers (Harrington, 1995). Compared to workshops or seminars, case-based learning may be a more appropriate format to conduct learning analytics professional development because it focuses on applying conceptual or theoretical knowledge to create practical pedagogical solutions. Goeze, Zottmann, Vogel, Fischer, and Schrader (2014) applied case-based learning to train novice teachers' analytical competence to identify good and poor instructional practices based on teaching videos. The results showed that by observing various teaching practices in real teaching scenarios, even through videos, novice teachers could improve their abilities to examine effectiveness of instruction from both student's and teacher's perspectives. Case-based learning using teaching scenarios also bears opportunities for teachers to learn through problem-solving. Merseth (1990) suggested that this kind of professional development could be particularly useful for preservice teachers as they prepare to teach and tackle various scenarios in the classroom setting. Although case-based learning may be an ideal format for professional development for novice teachers, Shkedi (1998) cautioned that clear guidance and goals would be an important basis with regard to the openness of problems presented in case study.

Goeze et al. (2014) suggested that teachers' analytical competence is crucial to their teaching and students' learning. Teachers' analytical competence enables them to observe, analyze, and assess different teaching scenarios and it is the key to their teaching competence (p. 4). The ability to interpret the pedagogical situations in the teachers' own expertise domains is the determinant for teachers' teaching efficacy and variances in students' achievement (Berliner, 2001; Hattie, 2009). Ball and Cohen (1999) also argued that in order for teachers to assess their teaching accurately and attend to students' individual learning needs, it is important for teachers to evaluate their teaching not only from their own perspective but also from the students' perspectives. Hogan et al. (2003) compared experienced and novice teachers in terms of their ability to evaluate their own teaching and lesson planning. The authors found that novice teachers tended to apply primarily their own perspective as a teacher when interpreting the outcomes of their teaching, while the experienced teachers were able to balance both teachers' and students' perspectives. The ability to take different perspectives to analyze teaching performance is important but hard for novice teachers, due to their lack of teaching experiences.

In this dissertation research, I focused on integrating professional development with a teaching scenario to train novice teachers in learning analytics knowledge and skills. By using a teaching scenario, this kind of professional development exposes novice teachers to real-world teaching scenarios and allows them to experience various perspectives when considering their pedagogical approach. Synthesizing learned pedagogical theories to their teaching practice and applying the skills learned from learning analytics may help novice teachers to better assess their own teaching and student learning and, in turn, increase their teaching efficacy and teacher resiliency.

Chapter III

LEARNING ANALYTICS SURVEY STUDY

The learning analytics survey study was developed and administered to address the first research question: What are the challenges, perspectives, and usage patterns of learning analytics in STEM teachers/educators, and how does that influence their teaching efficacy? This research question was examined further through the following sub-questions:

1. How commonly do in-service and preservice STEM teachers use learning management systems and learning analytics?
2. What are the barriers to teachers in using learning analytics?
3. What are the in-service and preservice teachers' perceptions of their technological pedagogical knowledge and teaching efficacy?
4. How are these barriers and usage of learning analytics related to in-service teachers' perceptions of their technological pedagogical knowledge and teaching efficacy?

Methodology

The data for this survey study were collected from volunteer participants on two occasions: once in Spring 2019 and once in Fall 2019 during an annual college-wide academic festival event where alumni, faculty, and students in the field of education come together to participate in symposia, talks, workshops, panels, display/demos, and hands-on workshops.

Participants

A total of 72 participants voluntarily participated in this survey study. Forty-seven of the participants were in-service teachers who were teaching as full-time teachers. Another 16 participants were former teachers (e.g., retirees, left the teaching profession and went on to other educational sectors, and taking time off from teaching to pursue an advanced degree). The remaining nine participants were preservice teachers in math education. In the in-service teacher group, excluding one participant who did not share gender information, 76% were females and 24 % were males. The average age of the in-service teacher group was 38.9 years old. Also, 68.1% of in-service teachers were teaching at elementary school, 10.6% were teaching at middle schools, and 23.4% were teaching at high school. In the former teacher group, 75% were females and 25% were males. The average age of this former teacher group was 35.5 years old. In the preservice teacher group, excluding one participant who did not share gender information, 67% were females and 33% were males. The average age of this teacher group was 25.7 years old.

Procedure

Participants were recruited on-site through announcement and word-of-mouth at the annual college-wide academic festival event. Interested participants were asked to give consent and then seated to fill out the questionnaire. On average, participants spent about 5 minutes to complete the survey.

Measures

There were three separate surveys totaling 31 questions. The three surveys administered were: the Learning Analytics Survey, the Technological & Pedagogical Knowledge (TPK) questionnaire, and the Teaching Efficacy questionnaire. Each measure is described in detail below. Measures are also included in the Appendix C.

Learning Analytics Survey. The Learning Analytics Survey consists of 19 questions: seven Demographic questions (e.g., gender, age, teaching subject, grade level, thought about quitting); eight questions on usage of Learning Analytics (LA) and Learning Management Systems (LMS); three questions on School Leadership; and one open-ended question asking whether the participant had ever considered leaving the teaching profession.

The Learning Analytics (LA) and Learning Management Systems (LMS) questions (Question numbers 8-12) examined usage patterns, challenges, and barriers in using learning analytics in LMS, as well as teachers' expectations of what LMS analytics can or cannot do for their teaching. The questions used a 5-point Likert scale, from *strongly disagree (1)*, *no opinion (3)*, to *strongly agree (5)*. Some example questions were:

- *"Which learning management system (LMS) do you use for teaching?"*
- *"Which LMS learning analytics functions do you use?"*
- *"What are the major reasons that you are not using LMS data analytics?"*
- *"Which aspect(s) of student learning do you think LMS data can reflect?*"

Questions that examined challenges and barriers were based on literature that indicated various reasons for teachers' reluctance to use LMS learning analytics (e.g., lack of computer skills, objection from parents). Similarly, questions on what kind of expectations teachers have towards LMS learning analytics and how it can assist their curriculum/instructional design (Question numbers 13-15) were also generated from past literature in this area (e.g., know students' learning process, identify at-risk students). Example questions included:

- "*LMS data analytics provide useful information to improve my teaching.*"
- "*LMS data analytics make curriculum/instruction design more effective.*"

Questions on school leadership (Question numbers 28-30) asked participants about their personal perceptions of workload at school and support they gained through professional development and school leadership. These questions were asked because past research has indicated that teachers' perceptions of workload and/or support leadership could impact their adoption of technologies in teaching (Buabeng-Andoh, 2012). These questions included:

- *"How do you feel about your workload at school?"*
- *"I feel that my school provides support in professional development for improving teaching."*
- *"I feel that my school leadership is supportive of implementing new technologies for improving teaching."*

The questions used a 5-point Likert scale.

The last open-ended question asked participants: *"Have you thought about quitting being a teacher? If so, when (e.g., 1st year, 2nd year of teaching) and why?"* This question was asked to see if teacher burnout occurs in the beginning years, as suggested by past literature. A blank text box was used for the participants to write their responses.

Technological and Pedagogical Knowledge (TPK) Questionnaire. The Technological & Pedagogical Knowledge (TPK) Questionnaire consists of four questions (Question numbers 16 to 19) that measure how teachers use technologies in their teaching and how they see technology as a way to change instruction. The measure from Banas and York (2014) is an adjusted version from the original TPACK questionnaire developed by Schmidt et al. (2009). The reliability of this measure has been well established (Cronbach's alpha = .84) (see the literature review for more details on the original TPACK questionnaire). Banas and York's (2014) TPK measure was administered because the selected questions were more relevant to the case study that focused on teachers' integration of technology (i.e., Learning Management Systems-LMS) in teaching. This TPK was administered to measure teachers' perceived ability to use LMS and Learning Analytics (LA) technologies in their teaching and student learning. Example questions included:

- *"Do you feel you can choose technologies that enhance your teaching approaches for a lesson?*"
- *"Do you feel you can choose technologies to enhance students' learning for a lesson?"*

The responses were set using a 5-point Likert scale going from *strongly disagree (1)*, *no opinion (3)*, to *strongly agree (5)*.

Teaching Efficacy Questionnaire. Questions 20 to 27 concerned participants' perceived teaching efficacy. The teaching efficacy questionnaire was established by

Tschannen-Moran and Hoy (2001) and measures teachers' efficacy and confidence in instructional practices and student engagement. The measure has good reliability (Cronbach alpha = .91) and is often used to survey preservice and in-service teachers. Some example questions included:

- *"To what extent can you use a variety of assessment strategies?"*
- *"To what extent can you craft good questions for your students?*"
- *"How well can you implement alternative strategies in your classroom?"*

Based on the original measure, the responses to these questions were arranged by using a 9-point Likert scale going from *nothing (1), very little (3), some (5), quite a bit (7)*, and *a great deal (9)*.

Results

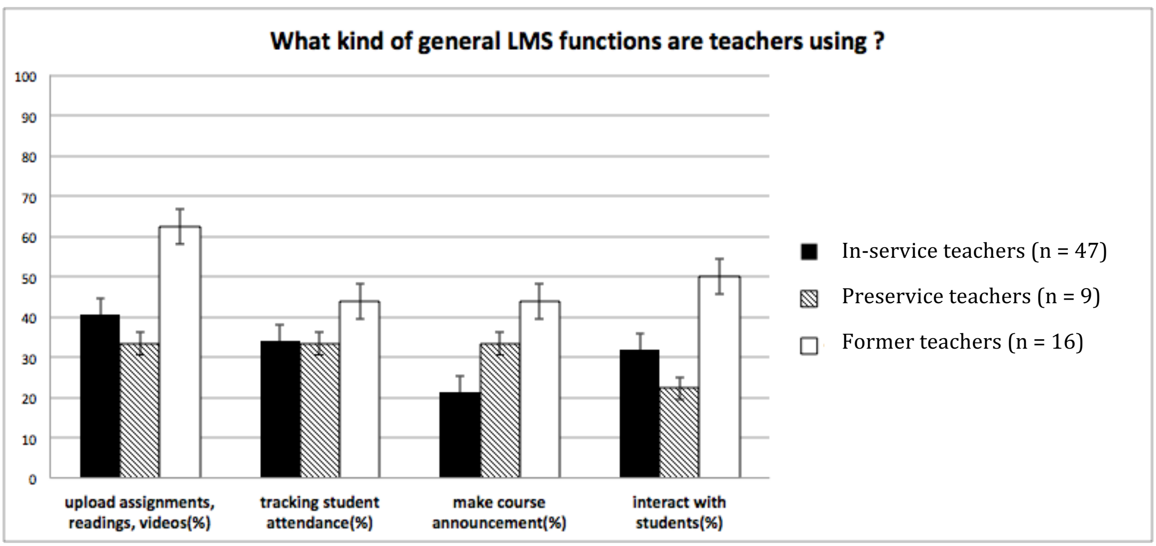
The learning analytics survey study was developed and administered to address the first research question: *What are the challenges, perspectives, and usage patterns of learning analytics in STEM teachers/educators, and how does that influence their teaching efficacy?* The results from the learning analytics survey were examined closely by answering each of the sub-questions listed below.

Sub-question 1. How Commonly Do In-Service and Preservice STEM Teachers Use Learning Management Systems and Learning Analytics?

Usage gap between in-service and preservice teachers regarding LMS. Regarding the use of LMS, in-service teachers had a higher tendency to use different LMS functions in general (see Figure 1). For the function of *upload assignment, reading, videos, etc.*, about 40.4 % of the in-service teachers have used this function, while about

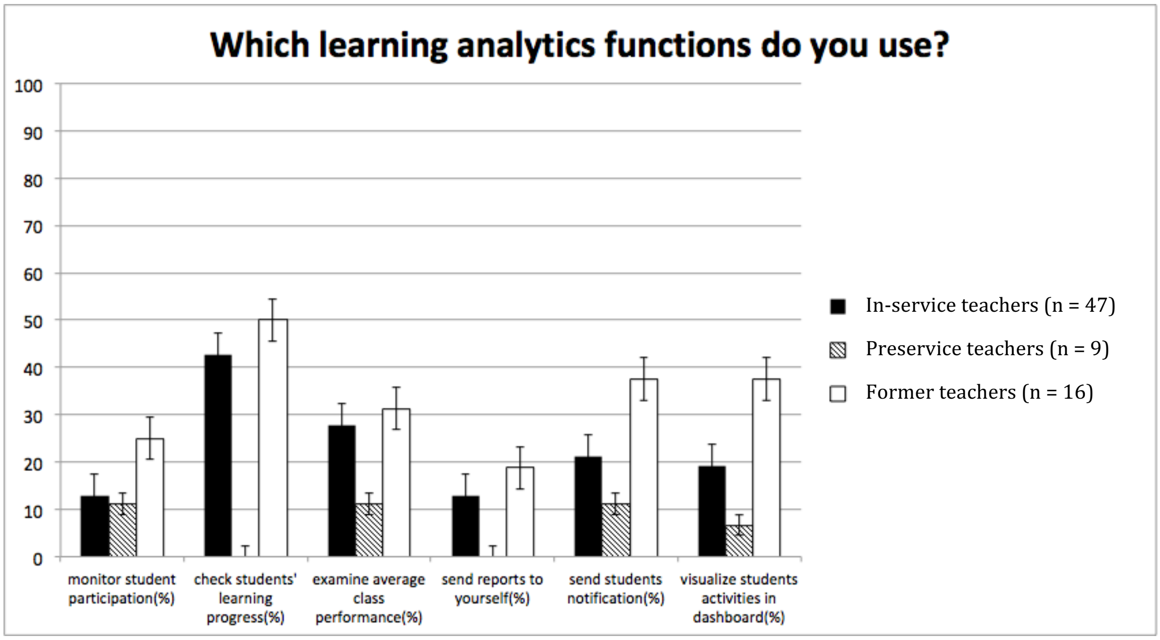
33.3% of the preservice and 62.5% of the former teachers have used this function. For the function of *tracking student attendance*, 34% of the in-service have used it and about 33.3% of the preservice and 43.8% of the former teachers have used the same function. Notably, with regard to *making course announcements*, 21.3% in-service teachers have used this function, which is lower than 33.3% for the preservice teachers and 43.8% for the former teachers. For the function of *interact with students*, 31.9% of in-service, 22.2% preservice, and 50% former teachers have used this function.

Figure 1. Comparison of General LMS Functions Use (%)



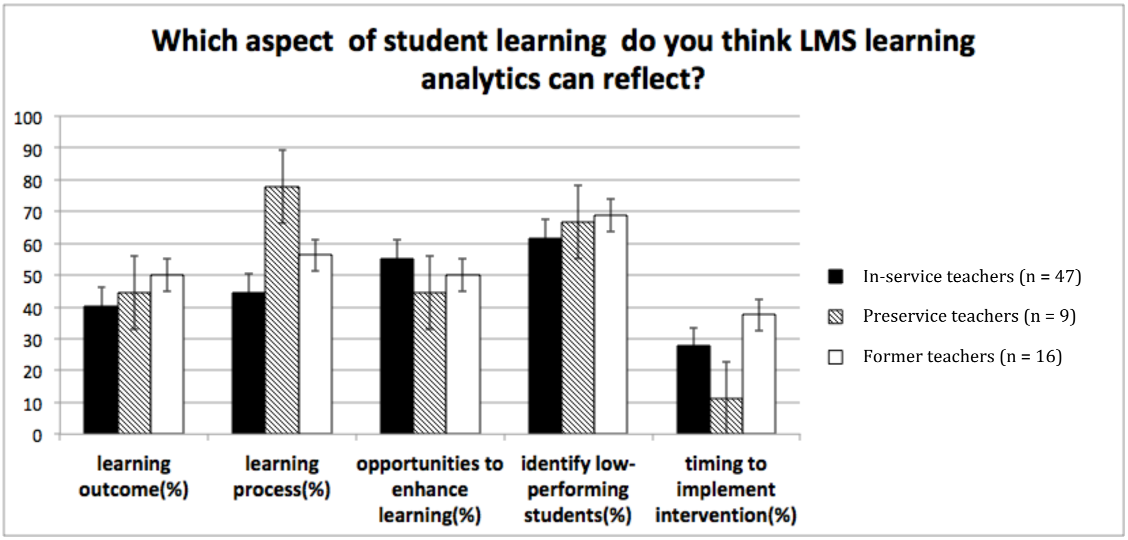
With regard to the usage of learning analytics (see Figure 2), the results showed that the in-service teachers had a higher tendency to use different types of learning analytics functions, compared to the preservice teachers. Particularly, the largest discrepancy between those two groups existed in the option of *check individual student's* *learning progress* (43.6% vs. 0%), *examine average class learning performance* (27.7% vs. 11.1%), and *send report to themselves (i.e., teachers)* (12.8% vs. 0%).

Figure 2. Comparison of Learning Analytics Features Use (%)



When asked about the aspects of student learning that LMS data can reflect (see Figure 3), preservice teachers had a higher tendency to believe that LMS learning analytics can reflect *learning outcomes* (preservice: 44.4%; in-service: 40%) and *learning process* (preservice: 77.8%; in-service: 44.7%). Preservice teachers also considered LMS learning analytics can *identify low-performing students* more than in-service students (preservice: 66.7%; in-service: 61.7%). However, for *opportunities to enhance learning* and *timing to implement intervention,* in-service teachers gave a higher rating score than the preservice teachers.

Figure 3. Aspects of Student Learning That Teachers Think LMS Data Can Reflect



Most commonly used LMS platforms. The most frequently used LMS platforms for in-service teachers were Google Classroom (27.7%) and Class Dojo (19.1%). For preservice teachers, they used Google Classroom (66.7%) and Canvas (22.2%) most frequently. For former teachers, they also used Google Classroom (25.5%) and Canvas (25.5%) most frequently.

Sub-question 2. What Are the Barriers to Teachers in Using Learning Analytics?

Barriers to using LMS learning analytics. With regard to the reasons for not using learning analytics in LMS (see Table 1), some of the obvious barriers to in-service and preservice teachers were *I don't know if the LMS I am using has data analytics functions* (in-service: 17%; preservice: 22%); *not so familiar with computer skills* (in-service: 17%; preservice: 22%); *not so familiar with math/statistical knowledge* (in-service: 11%; preservice: 10%); and *objection from students* (in-service: 15%; preservice:

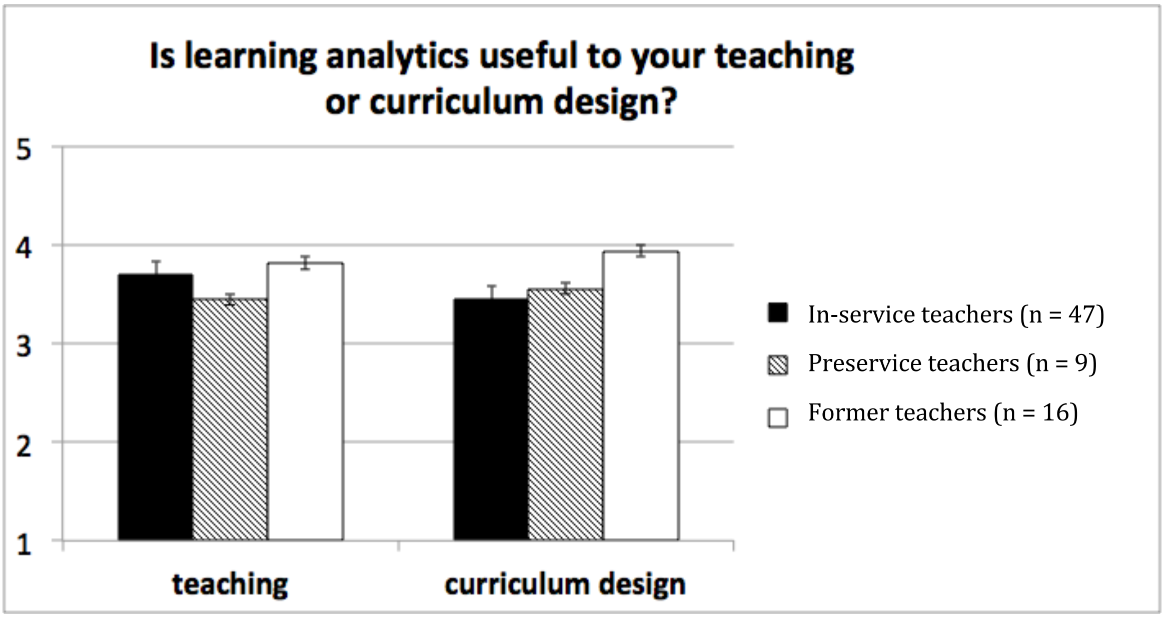
11%). Also, *objection from parents* was also an obvious reason for in-service teachers not to use LMS Learning Analytics (16%).

Table 1. *Reasons for Not Using LMS Learning Analytics*

Reason	Group	Count/ Total
I don't know if the LMS I am using has data analytics functions	In-service	8/47 (17%)
	Preservice	2/9 (22%)
	Former	2/16 (13%)
Objection from students	In-service	15/47 (15%)
	Preservice	1/9 (11%)
	Former	1/16 (6%)
Objection from parents	In-service	8/47 (16%)
	Preservice	0/9 (0%)
	Former	0/16 (0%)
Not so familiar with computer skills	In-service	8/47 (17%)
	Preservice	2/9 (22%)
	Former	3/16 (19%)
Not so familiar with math/statistical knowledge	In-service	5/47 (11%)
	Preservice	1/9 (10%)
	Former	1/16 (6%)
LMS data may be used against me on my work performance evaluation	In-service	2/47 (4%)
	Preservice	0/9 (0%)
	Former	1/16 (6%)
LMS data can't truly reflect students' learning outcomes	In-service	4/47 (9%)
	Preservice	1/9 (11%)
	Former	1/16 (6%)

Perceived usefulness of LMS learning analytics between in-service and preservice teachers. With regard to the perceived usefulness of learning analytics (see Figure 4), on a scale from 1 (strongly disagree) to 5 (strongly agree), the in-service teachers gave an average score of 3.7 (*No opinion–Agree*) and 3.4 (*No opinion–Agree*) when they considered the usefulness of learning analytics in teaching and instructional design, respectively. For preservice teachers, their responses were 3.4 (*No opinion–Agree*) and 3.6 (*No opinion–Agree*) when they considered the usefulness of learning analytics in teaching and instructional design.

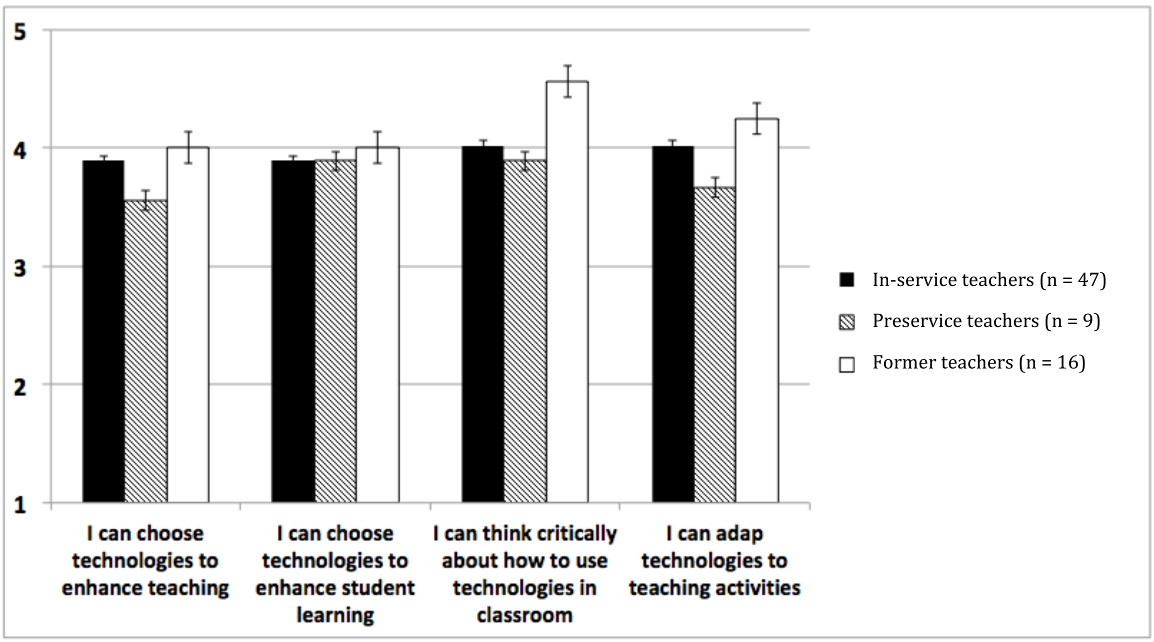
Figure 4. Is LMS Learning Analytics Useful in Teaching/Curriculum Design?



Sub-question 3: What Aare the In-Service and Pre-Service Teachers' Perceptions of Their Technological Pedagogical Knowledge and Teaching Efficacy?

Comparison of Technological Pedagogical Knowledge (TPK). Participants' TPK was measured on a 5-point Likert scale. Based on descriptions of TPK questions, the scale went from 1 (*strongly disagree)* to 5 (*strongly agree)* and 3 suggested *no opinion.* The results indicated that although there was some variation in TPK between in-service and preservice teachers, the difference in general was not obvious. While in-service teachers scored higher on all of the TPK questions, this indicated they were more confident about using technologies in teaching than the preservice teachers. It was found that there existed a larger gap of the average TPK score between preservice and in-service teachers on the first and the last question (TPK-Q1 and TPK-Q4). These two questions were *"Do you feel you can choose technologies that enhance your teaching approaches for a lesson?"* and "*Do you feel you can adapt different technologies to different teaching activities?"* The difference between the two groups for TPK-Q1 and TPK-Q4 was about 0.3 (see Figure 5).

Figure 5. Comparison of Technological Pedagogical Knowledge (TPK)



Comparison of teaching efficacy. Participants' teaching efficacy was measured on a 9-point Likert scale. The scale for this measure went from 1 (*nothing)* to 9 (*a great deal)*, with the middle point of 5 indicating *some.* When comparing preservice teachers' teaching efficacy scores to in-service teachers' scores (see Figure 6), the results showed that for all of the eight teaching efficacy questions in general, preservice teachers had lower scores than in-service teachers. It was also found that on questions 1, 6, 7, and 8 (TE-Q1, -Q6, -Q7), the two groups of teachers differed the most regarding their scores.

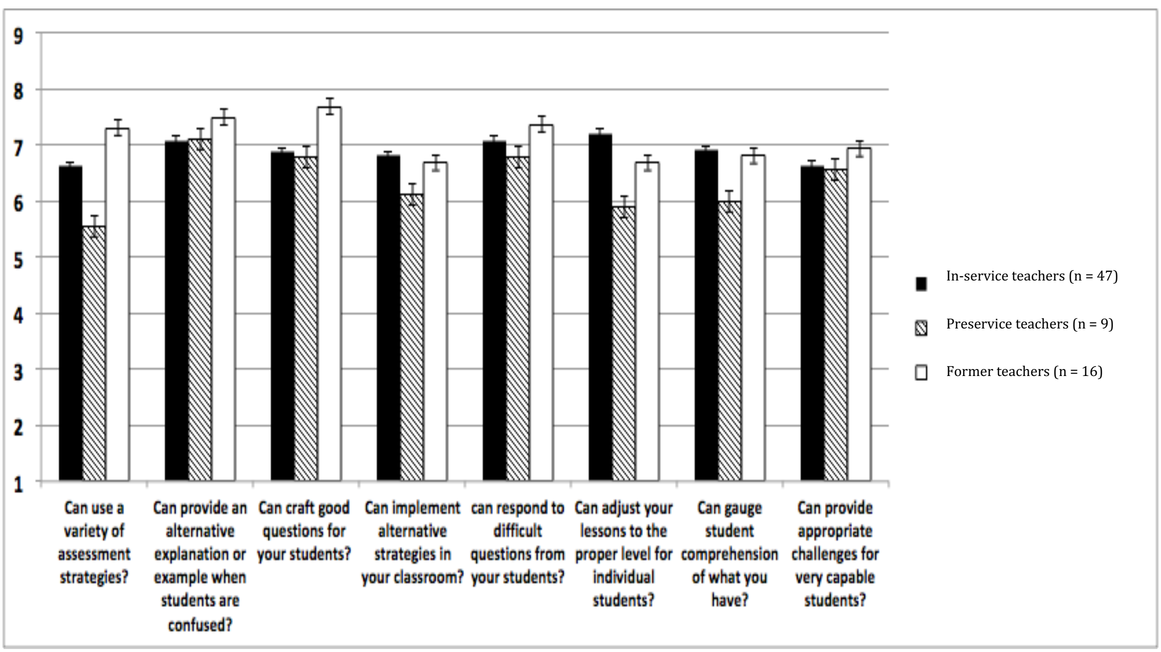
For these three questions (listed below), in-service teachers exhibited much higher confidence than preservice teachers.

TE-Q1. To what extent can you use a variety of assessment strategies?

TE-Q6. How much can you do to adjust your lessons to the proper level for individual students?

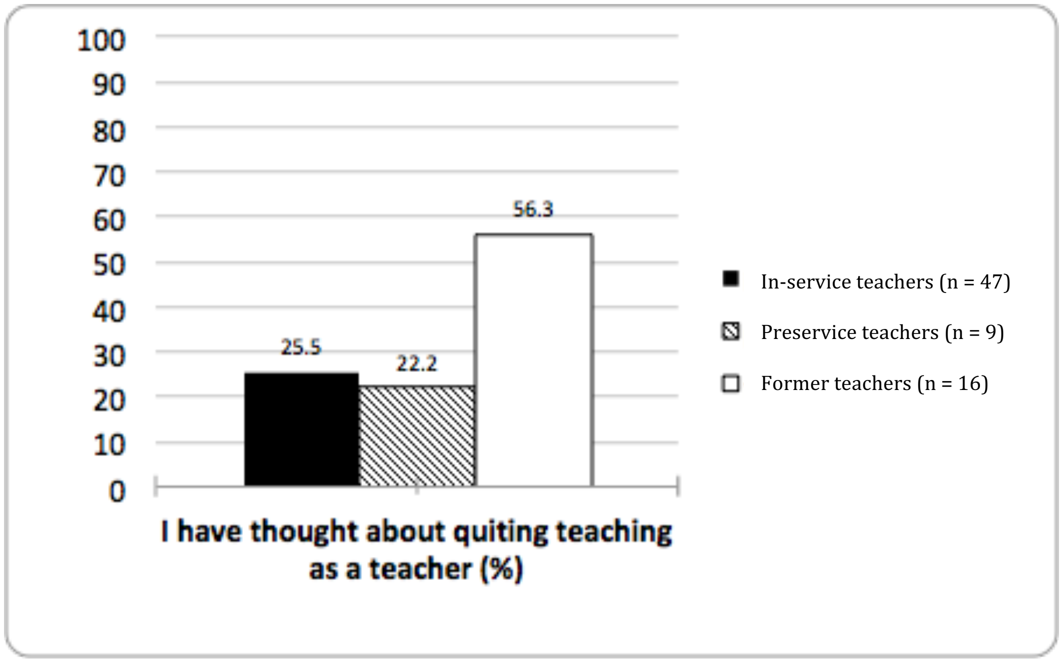
TE-Q7. To what extent can you gauge student comprehension of what you have taught?

Figure 6. Comparison of Teaching Efficacy



Intention to quit teaching. The results showed that about a quarter of the in-service teachers have had the intention to quit teaching, and about one-fifth of the preservice teachers have thought about quitting teaching. Notably, over 50% of the former teachers (e.g., retirees, left the teaching profession and went on to other educational sectors, and taking time off from teaching to pursue an advanced degree) have had the intention to quit teaching (see Figure 7).

Figure 7. Comparison of Intention to Quit as a Teacher



The qualitative feedback from the participants provided useful insights to explain this discrepancy between different groups of participants regarding the timing and major reasons why they wanted to quit teaching. Most of the preservice teachers expressed that they liked teaching and have not considered quitting teaching. However, for preservice teachers, some of the reasons for wanting to quit were as follows:

> *"I feel my teaching is never perfect." (preservice teacher-03)*
>
> *"Teaching is stressful." (preservice teacher-03)*
>
> *"Students complain a lot." (preservice teacher-03)*
>
> *"I am considering becoming a professor at college to teach in higher education." (preservice teacher-04)*

Most of the in-service teachers expressed that they liked teaching and have not considered quitting teaching. However, some teachers shared the reasons why they would want to quit in the following:

> *"Not yet." (in-service teacher-03)*

> *"Yes, sometimes I feel teaching is too demanding." (in-service teacher-07)*

For those who have stopped teaching and are pursuing advanced degrees in education, the data showed that their intention to quit teaching occurred mostly in the beginning years and later in their teaching career. Some of the former teachers' reasons to quit teaching were:

> *"I wanted to quit teaching at the first and the twentieth year of being a teacher." (former teacher-04)*

> *"About seven years of teaching I wanted to quit because I felt overworked and the administration is corrupted." (former teacher-07)*

> *"I wanted to quit the first year of teaching. The elementary system is too rigid and hard to change." (former teacher-10)*

> *"First year, when I felt frustrated when students ignored me." (former teacher-14)*

> *"Second year, because of the lack of career progression options." (former teacher-15)*

> *"Yes, because of it is difficult to manage a large classroom of 30-50 kids." (former teacher-16)*

Sub-question 4: How Are These Barriers and Usage of Learning Analytics Related to In-Service Teachers' Perceptions of Their Technological Pedagogical Knowledge and Teaching Efficacy?

Further statistical analysis was conducted with the 47 in-service teachers to see if there were any correlations across different measures. Only the in-service teacher data were used in the analysis due to the larger sample size (n = 47), compared to the number of participants for preservice (n = 9) and former teachers (n = 16). Although there were 16 participants in the former teacher group, due to the limitation in the survey questions, it was not clear how long these teachers had been away from teaching. Because of the potential variation in the amount of time away from teaching between all the former teachers, their data were not analyzed for correlation analyses. Also, because the continuous data on different measures in the survey used different scales, the data were first standardized, and all correlation analyses were conducted based on Z-scores.

Perceived usefulness of LMS/learning analytics. The results showed that there was a strong positive correlation (Pearson r = 0.73, p-value = 0.00) between in-service teachers' perceived usefulness of LMS learning analytics in teaching and curriculum/ instructional design (i.e., *LMS data analytics provide useful information to improve my teaching* and *LMS data analytics make curriculum/instructional design more effective*).

School workload, professional development, support from school leadership. On the administrative side, the results showed that in-service teachers' perceived school workload had a positive correlation with their perceived professional development support (i.e., *I feel that my school provides support in professional development for improving teaching*) (Pearson r = 0.4, p-value = 0.01). Meanwhile, perceived professional development support also had a positive correlation with perceived support from school leadership (i.e., *I feel that my school leadership is supportive of implementing new technologies for improving teaching*) (Pearson r = 0.56, p-value = 0.00). However, it was found that in-service teachers' perceived workload had a moderate negative correlation with their perceived usefulness of LMS learning analytics in teaching (Pearson r = -0.38, p-value = 0.01).

TPK and teaching efficacy. With regards to TPK and teaching efficacy questions, although there was no significant correlation between the average teaching efficacy and average teaching efficacy score, there were some insightful findings when examining correlations between questions in the two measures separately. Specifically, there was a positive correlation between the first question of TPK (i.e., *Do you feel you can choose technologies that enhance your teaching approaches for a lesson?*) and the eighth question of teaching efficacy (i.e., *How well can you provide appropriate challenges for very capable students?*) (Pearson r = 0.32, p-value = 0.03). There was also a positive relationship between the third TPK question (i.e., *Do you feel you can think critically about how to use technology in your future classroom?*) and the second teaching efficacy question (i.e., *To what extent can you provide an alternative explanation or example when students are confused?*) (Pearson r = 0.29, p-value = 0.049). The third TPK question also had a positive relationship with the fourth teaching efficacy question (i.e., *How well can you implement alternative strategies in your classroom?*) (Pearson r = 0.31, p-value = 0.03).

Number of LMS/learning analytics functions use. In the survey study, in-service teachers were asked to mark each kind of LMS and learning analytics functions they have used in teaching. Examples of LMS functions included *upload assignments, readings, videos, track students' attendance, create tests,* and the like. Also, examples of learning analytics functions included *monitor students' course participation, check individual student's learning progress, predict students' learning outcomes,* and so on. The total number of functions use was tallied for LMS and learning analytics separately.

The correlation analysis exhibited some informative results between the number of LMS/learning analytics functions use and other measures.

First, for in-service teachers, there was a strong positive correlation between the number of LMS functions and learning analytics functions they used (Pearson $r = .71$, p-value = 0.0). In-service teachers' total number of learning analytics functions use also had a positive correlation with the number of learning aspects they thought LMS can reflect (Pearson $r = .41$, p-value = 0.00). Different learning aspects in the survey question included *learning outcome, learning process, identification of low-performing/at-risk students*, and so on. An important factor that impeded in-service teachers to use LMS or learning analytics seemed to be their school workload. The results showed that perceived workload had a negative correlation with both the number of LMS functions use (Pearson $r = -.29$, p-value = 0.046) and learning analytics functions use (Pearson $r = -.38$, p-value = 0.01).

Correlations between number of LMS/learning analytics functions use and TPK. The results of correlation analysis also showed that there was positive correlation between the number of LMS functions in-service teachers used and their TPK ($r = 0.36$, $p = 0.01$). However, between the number of learning analytics functions in-service teachers used and their TPK, there was no significant correlation (Pearson $r = 0.24$, $p = 0.11$).

Correlations between number of LMS/learning analytics functions use and teaching efficacy. For teaching efficacy, the results showed that teaching efficacy had a positive correlation with the number of LMS functions used by the in-service teachers (Pearson $r = 0.35$, $p = 0.02$). Also, it was found that teaching efficacy had a positive correlation with the number of learning analytics functions in-service teachers used (Pearson $r = 0.31$, $p = 0.04$).

In-service teachers' perceptions of LMS learning analytics usefulness, actual use of LMS learning analytics, and TPK/teaching efficacy. The correlation analysis showed insightful results when taking into account the influence of in-service teachers' perceptions of LMS learning analytics usefulness. Previous correlation results demonstrated a positive correlation between how many LMS/learning analytics functions in-service teachers used and their TPK. When I further analyzed the data by separating the 47 in-service teachers into two groups, namely, those who perceived LMS learning analytics useful in teaching/curriculum/instructional design versus those who did not, the two groups of in-service teachers demonstrated different patterns regarding the correlation between their use of LMS learning analytics and their TPK.

Specifically, 29 out of the 47 in-service teachers had positive perceptions that the LMS learning analytics was helpful in their teaching (i.e., those who marked higher than three points *[no opinion]* for LMS learning analytics usefulness); the number of LMS functions they used correlated positively with their TPK (Spearman $r = 0.44$, $p = 0.02$) and teaching efficacy (Spearman $r = 0.5$, $p = 0.01$). In contrast, 18 out of the 47 in-service teachers did not have positive perceptions of LMS learning analytics as helpful in their teaching (i.e., those who ranked lower than three points *[no opinion]* for LMS learning analytics usefulness); the number of LMS functions they used did not correlate with their TPK (Spearman $r = 0.2$, $p = 0.42$) or teaching efficacy (Spearman $r = 0.23$, $p = 0.37$).

In addition to the number of LMS functions, correlation between the number of LA functions used by in-service teachers and their TPK and teaching efficacy also seemed to be influenced similarly by this perception of usefulness of LMS learning analytics.

For in-service teachers who had positive perceptions of LMS learning analytics as helpful in their teaching, the number of learning analytics functions they used correlated positively with their TPK (Spearman $r = 0.39$, $p = 0.04$) and teaching efficacy (Spearman $r = 0.45$, $p = 0.02$). On the contrary, for those who did not perceived LMS learning analytics as helpful in their teaching, the number of learning analytics they used did not correlate with their TPK (Spearman $r = 0.03$, $p = 0.9$) or teaching efficacy (Spearman $r = 0.35$, $p = 0.16$).

The influence of the perception of usefulness of LMS learning analytics in curriculum/instruction design (instead of in teaching) resonated with the above patterns. For the in-service teachers who perceived LMS learning analytics helpful in curriculum/instruction design (i.e., 27 out 47 in-service teachers), the number of LMS functions they used correlated positively with their TPK (Spearman $r = 0.5$, $p = 0.01$) and teaching efficacy (Spearman $r = 0.51$, $p = 0.01$). Similarly, for the use of learning analytics functions, those who perceived LMS learning analytics as helpful in their curriculum/instruction design, and the number of learning analytics functions they used, correlated positively with their TPK (Spearman $r = 0.48$, $p = 0.01$) and teaching efficacy (Spearman $r = 0.44$, $p = 0.02$). In contrast, for the in-service teachers who did not perceive LMS learning analytics as helpful in curriculum/instruction design (i.e., 20 out of 47 in-service teachers), the number of LMS functions they used did not correlate with their TPK (Spearman $r = 0.2$, $p = 0.41$) or teaching efficacy (Spearman $r = 0.12$, $p = 0.61$). Also, the number of learning analytics functions they used did not correlate with their TPK (Spearman r = 0.01, p = 0.99) or teaching efficacy (Spearman r = 0.31, p = 0.19).

In sum, based on the above correlation results, although using more LMS or learning analytics functions was correlated with higher TPK and teaching efficacy for the in-service teachers, it appeared that having the perception that LMS learning analytics was useful in teaching or curriculum design was the prerequisite for this correlation to be established.

Discussion

This survey study revealed several important findings that I review in this discussion section. I discuss each key finding separately below.

Gap Between Preservice and In-service Teachers Regarding LMS Use

Regarding the use of LMS, it is not surprising that in-service teachers have used more different general LMS functions as well as LMS learning analytics functions compared to preservice teachers. The survey results suggested that Google Classroom, Class Dojo, and Canvas are the three LMS that preservice and in-service teachers used most frequently. Google Classroom and Canvas generally provide LA tools such as charts, tables, graphs, and other data visualizations to give teachers insights into students' learning performance and progress through data dashboards. Only a few preservice (6.7%) and a small portion of in-service teachers (19.1%) indicated that they used such functions, but many teachers still claimed they have used learning analytics to examine students' learning performance and progress. Such response revealed a gap between what learning analytics function teachers *say they are using* and the functions they are *actually using.* Both preservice and in-service teachers seemed to believe they were using learning analytics in LMS while in reality they were not.

Another interesting finding emerged. When in-service teachers were asked *"Which aspects of student learning do you think LMS data can reflect?"*(see Figure 3), their responses resonated with the earlier question, *"Which learning analytics function do you use?"* (see Figure 2). This implied that in-service teachers had some sense of which learning analytics tools can potentially reflect or monitor students' learning outcomes and learning processes. In contrast, nearly none of preservice teachers noted any use of LMS function (Figure 2), but they still believed (more than in-service teachers) that LMS data can truly reflect students' learning processes and learning outcomes (Figure 3).

Perhaps preservice teachers are more optimistic about the potential of LMS learning analytics in assessment and teaching, even without much prior experience in using it. Another explanation could be that in-service teachers are more aware of the limitations of LMS and learning analytics with regards to how much such tools can reflect students' learning outcomes and learning processes. Such perceptions may come from their own user experience as in-service teachers and the complexities surrounding student learning.

Reasons for Not Using Learning Analytics

In contrast to the wide range of potential barriers noted from the literature, only a small portion was selected by in-service and preservice teachers as potential barriers to using LMS and learning analytics (see Table 1). It is also interesting to discuss the similarities and differences in the barriers perceived by in-service and preservice teachers. The first similarity is that both preservice and in-service teachers reported they were not aware if there was any learning analytics functions in the LMS systems they were using. Google Classroom and Canvas (the two major LMS systems most commonly used by the teachers) do have different learning analytics functions such as data dashboards, data visualization features, and student performance tracking, but the preservice and in-service teachers' responses seemed to imply they may not be familiar with such functions. Other similarities between preservice and in-service teachers were perceived barriers due to the lack of computer skills and objection from students. This may suggest that for both preservice and in-service teachers alike, their teacher education program or professional development may not have familiarized them to utilize LMS and learning analytics functions. Also, the perceived objection from students may also suggest that teachers have to work on communication with students to build more trust with regards to using learning analytics tools to assess students' learning.

Barriers perceived by in-service but not preservice teachers included lack of math/statistics knowledge and objection from parents. This may suggest that in-service teachers may not have had enough statistical training, or they needed to refresh statistical knowledge after they graduated from their teacher education program. The in-service (but not preservice) teachers' concern about parents' objection in using learning analytics showed that experienced teachers were generally more concerned about their parent-teacher relationships and communication (Ingersoll, 2000). This also suggested that in-service teachers need to be able to explain to parents how learning analytics will be used to assess student learning objectively.

Technological Pedagogical Knowledge (TPK): Gap Due to Experience of Using Technologies to Teach

The results indicated that in-service teachers have a higher average (see Figure 6) on most of the TPK questions. Initially, the anticipation was that preservice teachers, who are generally younger in age than in-service teachers, may be more technology-savvy, but the results showed preservice teachers were less confident about the pedagogical use of technology. When comparing the responses from the four TPK questions, the results showed a large gap in the average TPK score between preservice and in-service teachers on the first and last questions (TPK-Q1 and TPK-Q4). These two questions were *"Do you feel you can choose technologies that enhance your teaching approaches for a lesson?"* and *"Do you feel you can adapt different technologies to different teaching activities?"* For these two questions, participants were asked to refer to their classroom teaching practice/activities, which may be the reason for the differences between preservice and in-service teachers. Because classroom teaching was limited with preservice teachers, the lack of experience using technology to teach may have led them to feel less prepared.

Teaching Efficacy: Gap due to Lack of Confidence of Assessing Students' Learning

When comparing teaching efficacy scores between preservice and in-service teachers (see Figure 7), preservice teachers had lower scores than in-service teachers. Results seemed to reflect the lack of confidence coming from limited teaching experience. After taking a closer look at each teaching efficacy question, the results showed that preservice and in-service teachers differed most on questions 1, 6, 7 (see

Table 2). It is worth noting that these three questions shared the element of "assessing student learning."

Table 2. *Categorization of Teaching Efficacy Measure Questions*

Questions That Have Student Learning Assessment Element
TE-Q1. To what extent can you use a variety of assessment strategies?
TE-Q6. How much can you do to adjust your lessons to the proper level for individual students?
TE-Q7. To what extent can you gauge student comprehension of what you have taught?
Other Questions (Non-Student Learning Assessment)
TE-Q2. To what extent can you provide an alternative explanation or example when students are confused?
TE-Q3. To what extent can you craft good questions for your students?
TE-Q4. How well can you implement alternative strategies in your classroom?
TE-Q5. How well can you respond to difficult questions from your students?
TE-Q8. How well can you provide appropriate challenges for very capable students?

For instance, *TE-Q1* asked if the participant could apply different assessment strategies, while *TE-Q6* asked if the participants could adjust lesson plans based on different knowledge levels for students. To do this effectively, teachers would have to be able to assess each student's learning process and performance correctly. Similarly, *TE-Q7* asked if participants could estimate that their students have understood their teaching. This question also involves the teachers' analytical competence to assess their own teaching as well as each student's learning performance. To help preservice teachers increase their teaching efficacy, it may be essential to increase their data analytical skills which will enable them to assess their teaching and student learning correctly and make appropriate pedagogical adjustments.

For the remaining questions that were not student assessment-related, the efficacy score did not vary significantly across the two groups.

Intention to Quit Teaching

The qualitative feedback for teachers who expressed they wanted to quit teaching can be summarized in a few major categories. The first category is contextual/ environmental factors, such as school culture or school system that is not supportive for the teachers and their teaching activities. The second category is about student/classroom management. Responses in this category are mostly about challenges dealing with a large class size, not being able to fulfill student needs, and student complaints. Further investigation is needed as data on student management were not gathered in this survey; however, it may be reasonable to assume that part of this issue could result from ineffective teacher practice. The third category is about the high demand and expectations placed on teachers. Responses in this category involved teachers' concerns about their own teaching performance and the high level of work stress from teaching. The findings from the response were aligned with previous literature on teacher turnover and teacher resiliency. Contextual and environmental factors should not be ignored, but more attention should be placed on teachers as individuals, as their teaching efficacy can affect work satisfaction, commitment, and intention to continue or quit as a teacher.

Insights from In-service Teachers

The correlation analysis focusing on in-service teachers demonstrated several important insights. First, it was found that for in-service teachers, the more LMS or learning analytics function they used, the higher TPK and teacher efficacy they would attain. This result based on correlation analysis did not assume any causality or any direction of influence. For in-service teachers, the use of LMS or learning analytics functions could potentially increase their TPK and teacher efficacy. On the other hand, this relationship could also be vice versa, where higher TPK or teaching efficacy could increase the use of LMS or learning analytics functions. Another important finding was in-service teachers' perceptions of the usefulness of LMS learning analytics in teaching and curriculum design. The correlation results showed that the perception of LMS learning analytics as useful seemed to be the prerequisite for the positive correlation between the use of LMS/learning analytics functions and their TPK/teaching efficacy. In other words, as previously assumed, if using LMS/learning analytics functions could increase teachers' TPK and teaching efficacy, then this connection may hold true only for those who have a prior perception that LMS learning analytics is helpful. The particular result could offer three important points for studies going forward. First, when teachers do not believe LMS learning analytics is helpful for their teaching or curriculum design, using LMS learning analytics functions, even very often, may just be a routine in their teaching work without the benefits of enhancing their TPK or teaching efficacy. Second, for professional development that aims to teach teachers to use LMS learning analytics and increase their TPK and teaching efficacy, both technical knowledge and teachers' confidence are important. The training content should focus on giving teachers both the technical skills as well as the confidence that LMS learning analytics can really be helpful in their teaching. The last insight is for novice teachers. Naturally, due to the lack of teaching experience, novice teachers may not have had much experience of using LMS or learning analytics in teaching. However, based on the findings about in-service teachers in the survey study, it may be safe to assume that if novice teachers are trained to utilize various learning analytics functions and also develop a perception that learning analytics is useful for their teaching, their TPK and teaching efficacy could also grow at the same time.

Summary

The results from the learning analytics survey not only revealed important information on how preservice and in-service teachers are utilizing LMS learning analytics, but also pointed out a potential solution to increase teachers' knowledge and application of learning analytics in teaching.

The results of the learning analytics survey helped identify the gaps in using learning analytics for both in-service and preservice teachers as well as different barriers in using learning analytics between the two groups of teachers. Compared to in-service teachers, preservice teachers' lack of teaching practice, lack of analytical competence to evaluate teaching outcomes, and low teaching efficacy appeared to be associated. Preservice teachers also seemed to lack the knowledge of what LMS learning analytics is capable of, although they were optimistic about using LMS learning analytics in their teaching. These results motivated me to design a training intervention based on a learning analytics professional development and an exploratory case study. The goal of this dissertation research was to examine if a learning analytics professional development would increase learning analytics knowledge and application for novice teachers. In addition, it is imperative to know if a learning analytics professional development can help novice teachers self-assess their teaching and also assess students' learning outcomes. If novice teachers become more capable of utilizing learning analytics in teachers in this manner, this may lead to an increase in their teaching efficacy and help reduce teacher turnover rates in the long run.

Chapter IV

CASE STUDY

Based on the findings from the survey study, I developed an exploratory case study to investigate the effects of professional development in learning analytics for novice teachers. The case study also examined if preliminary training in learning analytics influenced novice and former teachers' pedagogical knowledge (PK), technological pedagogical knowledge (TPK), teaching efficacy, and teacher resiliency. The case study was meant to explore the second research question, *Can learning analytics professional development assist teachers in developing skills to assess their own teaching practices and student performance, and how do such skills and training influence their teaching efficacy and teacher resiliency?* This research question was examined further through the following sub-questions:

1. Can professional development in learning analytics assist novice and former teachers in developing skills to assess teaching practices and student performance, and develop teachers' confidence in using learning analytics for teaching?
2. How does professional development in learning analytics influence novice and former teachers' pedagogical knowledge (PK) and technological

pedagogical knowledge (TPK), teaching efficacy, teacher resiliency, and their intentions to use learning analytics in their teaching?

Methodology

This case study implemented a professional development in learning analytics as an intervention. It was an exploratory study to examine the effects of this intervention on novice teachers' teaching efficacy, teaching resiliency, and learning analytics knowledge. The following section describes in detail the design and measures for this exploratory study.

Participants

There were five participants in this case study. All participants were Asian females and their ages ranged between 22 and 28 years old. Among the five participants, two were preservice math teachers. The remaining three participants were former English teachers who temporarily stopped teaching while pursuing their master's degrees. Pseudonyms are used for all five participants when describing their participation in this case study. Their background information is as follows.

Abby is a first-year preservice math teacher in a teacher education program. She comes with 2 years of math teaching experience at a learning center prior to entering the teacher education program, but has never taken on any formal teaching position. Currently she is gaining teaching experience through the practicum in her teacher education program. She has a statistics background and has worked as a statistician in the past. She has some experience using LMS (i.e., Canvas) only as a student and has never used any learning analytics functions.

Betty is a second-year preservice math teacher in a teacher education program. She has never taken on any formal teaching position in schools. She has some experience using LMS (i.e., Canvas, Class Dojo) as a student, and has never used any learning analytics functions.

Cindy is a graduate student and a former English teacher with 6 years of formal teaching experience in high school in Japan and the United States. She has experience using LMS (i.e., Moodle, Canvas, and Schoology) both as a student and a teacher, and has used learning analytics functions to monitor students' learning progress and outcomes.

Daisy is a graduate student and a former English teacher with 3 years of formal teaching experience at a middle school. She has experience using LMS (i.e., Blackboard) in her teaching for more than 2 years, and has used Blackboard to make course announcements, monitor students' learning outcomes, and make pedagogical decisions.

Ellen is a graduate student and a former English teacher with 6 months of formal teaching experience at an elementary school and adult learning center. She has experience using LMS (i.e., Canvas) only as a student but never while teaching.

The participants were recruited through announcement via school group email, flyers posted in public spaces at school, and word-of-mouth through a collegiate instructor with whom the author has a connection. There was a basic screening process to make sure participants either resided in a preservice teacher education program or had some formal teaching experience. The compensation for the participants was $45 upon finishing the 3 weeks of learning analytics professional development. No additional course credits, course bonus points, benefits, or rewards were given to the participants.

Procedure

After giving their consent to participate in this case study, each participant met one-to-one with the facilitator (i.e., researcher conducting the study) and completed the survey packet and a pretest (i.e., learning analytics to check for prior knowledge). All participants individually engaged with the facilitator in a one-to-one session covering the same learning analytics professional development for the next 3 weeks. Each week, the session lasted between 90-100 minutes, which consisted of a 40-50-minute tutorial/ review session and some time to answer surveys/scenario/interview questions (please refer to the Measures section). Each week, participants received a learning analytics professional development in a different topic area in learning analytics (see Table 3), and were then asked to fill out a survey packet and answer short interview questions. On completion of the Week 3 tutorial, participants were asked to fill out the survey packet, answer scenario questions, complete the posttest, and respond to a final exit interview. This completed the 3-week study. The next section explains a common structure across all tutorials and activities in the professional development. This section is followed by a week-by-week description of the tutorial session.

Table 3. *Learning Analytics Professional Development*

	Tutorial Topic and Skill	Procedure and Task	Duration (minutes)
Week 1	Topic: 1) Mean 2) Median Skill Training: - calculate mean & median values for students' scores - visualize mean & median scores with bar charts	Complete consent form & introduction	5
		Complete survey packet: 1) Demographic survey 2) Pedagogical knowledge (PK) 3) Technological knowledge (TPK) 4) Teaching Efficacy 5) Teacher Resiliency	10
		Complete Pre-test	25
		Read & respond to the scenario question in the teaching scenario (i.e., Megan's teaching scenario)	5
		Learning analytics tutorial (topic: mean & median)	40
		Participant answer three interview questions	5
Week 2	Topic: 1) Variance 2) Standard deviation 3) Correlation Skill Training: - Calculate variance & standard deviation for students' scores - Create a bar chart with mean and standard deviation for students' scores to exhibit the average and variation in students' performance on each learning activity - Calculate correlation coefficients between different student learning activities - Visualize correlation relationships with scatter plot and linear trendline	Review Week 1 tutorial content	10
		Learning analytics tutorial (topics: variance & correlation)	50
		Participant answer three interview questions	5
		Complete survey packet: 1) Pedagogical knowledge (PK) 2) Technological knowledge (TPK) 3) Teaching efficacy 4) Teacher resiliency	10

Table 3 (continued)

	Tutorial Topic and Skill	Procedure and Task	Duration (minutes)
Week 3	Topic: 1) Regression analysis 2) Regression coefficients 3) P-value 4) Comparison between correlation & regression Skill Training: - Fit regression model with input variables of learning activities and output variable of exam score - Interpret regression coefficients & p-value - Use regression model to predict students' exam scores in the future	Review Week 2 tutorial content	10
		Learning analytics tutorial (topic: regression analysis)	40
		Complete survey packet: 1) Pedagogical knowledge (PK) 2) Technological knowledge (TPK) 3) Teaching efficacy 4) Teacher resiliency	10
		Read & respond to the scenario question in the teaching scenario (i.e., Megan's teaching scenario)	5
		Complete posttest	40
		Participant answer three interview questions	5

Common Structure Across All Learning Analytics Tutorials and Activities

All the tutorials and activities in the 3-week learning analytics professional development had the following similar structure.

Engaging in one-to-one interactive session with facilitator. For all tutorials, each participant worked one-on-one with the facilitator who gave guidance (if needed) when participants followed the instructions and activities in the handouts. Occasionally, the facilitator asked for clarifications or questions about the case study scenario being studied. The facilitator had a flexible timeframe for each participant to complete the learning tasks, so participants could work at their own pace.

Hands-on learning analysis exercises. The weekly tutorials included hands-on data analysis exercises using Microsoft Excel. Each participant was first introduced to different learning analytics concepts and methods (i.e., mean, median, variance, correlation, regression), then worked on example questions, and were asked to explain their thought process so the facilitator could confirm participants had a good understanding of the topic. An example excerpt from the first week is presented below:

> *Mean is a value that represents an average of an array of numbers. To calculate a mean value, you will need to add the numbers together and divide it by the total count of numbers supplied. For example, the mean of (2,4,6) will be 4.*

Once the participant demonstrated good understanding of the concept and method, she would then continue with the tutorial, following the instructions in the handout and completing other learning analytics tasks using Microsoft Excel.

Learning analytics embedded in a teaching scenario. All the learning analytics tutorials, activities, and tasks were structured around a teaching scenario about a fictitious teacher colleague, Megan, who asked the participant for advice regarding her teaching plan and student performance. Participants were told they were presented with Megan's student data to help answer various learning analytics questions for Megan. The participants used these data to complete the tutorial activity, and then gave appropriate advice to Megan based on their findings. Below is an excerpt from the Week 1 tutorial on computing the mean value:

> *Your colleague Megan has been teaching a few mathematical concepts to her students. She has also collected several students' scores on various learning activities. She has shared these learning data with you. [Participants are guided to view the data in Excel.] Now Megan wants to know the mean score for each learning activity her students have finished. She wants to compare the mean of the quiz, assignment, and test scores across the three math concepts she has taught to her students. [Participants are guided to next steps to compute different mean score with the help from the author.]*

Participants were later be tested (i.e., posttest) on learning analytics concepts and methods from these tutorial activities and handouts. The next section briefly covers the week-by-week description of each tutorial session.

First week of learning analytics professional development. The first week of professional development involved an introduction to learning analytics and covered the topic on mean and median (see Table 3). Each participant was presented with a teaching scenario and then asked a general question (*"Megan wants to know how you find out your teaching skills and students' learning outcomes. After three weeks of learning analytics professional development, what would you say to Megan?"*) to see how the participants might go about explaining how they evaluated their teaching and student learning processes prior to experiencing any learning analytics tutorial (see Appendix D). The teaching scenario then went into more depth to describe the participants' fictional teacher colleague, Megan, and her motivation to use learning analytics to evaluate her teaching and students' learning. The participants were told that Megan had shared her student data and would need some help from the participants using learning analytics. The following is an excerpt from the teaching scenario.

> ***Learning Analytics Activity—Examine Students' Performance on Various Math Learning Activities***
>
> *Imagine you are an elementary school math teacher. Your teacher colleague, Megan, who is also teaching elementary math, has recently been introduced to a Learning Management System (LMS) at school through professional development. She is motivated to use students' learning data on the LMS to gain insights into students' learning outcomes. To experiment with this idea, Megan has collected students' data on various learning activities of a few mathematical concepts she has taught to her class, including quizzes, assignments, and tests.*

Although Megan is excited about the insights that students' learning data may bring on this LMS system, she is trying to understand how the different learning activities she designs help students learn different math concepts. Megan wants to know how you find out your teaching skills, and students' learning outcomes.

After participants responded to the scenario question (*"Megan wants to know how you find out your teaching skills and students' learning outcomes. What would you say to Megan?"*) the participants began the learning analytics tutorial for the first week (see Appendix F). The tutorial topics in the first week were mean and median in statistics. During the tutorial, the facilitator ensured the participants developed a solid understanding of the tutorial content. At the end of the /Week 1 tutorial, the participants were asked three interview questions on their perceived importance and relevance of the tutorial content to their own teaching, and how they might apply the learning analytics skills to their teaching (see Appendix E).

Second week of learning analytics professional development. The second week of professional development covered the topics variance, standard deviation, and correlation (see Table 3). The facilitator began the session by asking several review questions from the first week. The facilitator made sure the participants understood each question before asking the next question. If the participants gave incorrect responses, the facilitator would review relevant content from the previous week. The facilitator then revisited the ongoing teaching scenario with the fictitious colleague, Megan, and continued the learning analytics tutorial for the second week (see Appendix G). After the tutorial, participants were asked the same three interview questions on the relevance, importance, and application of this week's tutorial to their own teaching. Participants were then asked to complete a survey packet (see Appendix H) that consisted the pedagogical knowledge (PK), technological pedagogical knowledge (TPK), teaching efficacy, and teaching resiliency survey (see Table 3).

Third week of learning analytics professional development. The third week of professional development covered the topics regression analysis, regression coefficients, P-value, and comparisons between correlation and regression (see Table 3). The facilitator began the session asking several review questions from the second week. The facilitator made sure the participants understood each question before asking the next question. If the participants gave incorrect responses, the facilitator would review relevant content from the previous weeks. The facilitator then revisited the ongoing teaching scenario with their fictitious colleague, Megan, and continued the learning analytics tutorial for the third week (see Appendix I). After the tutorial, participants answered the same three interview questions on the relevance, importance, and application of this week's tutorial to their own teaching. Participants were then asked to respond to the general scenario question from the first week (*"Megan wants to know how you find out your teaching skills and students' learning outcomes. After three weeks of learning analytics professional development, what would you say to Megan?"*). This question was asked a second time to see how the participants responded after experiencing the 3-week tutorial. The participants then filled out the survey packet and continued on to the posttest (see Appendix J).

Measures

Several quantitative and qualitative measures were used in this exploratory case study. Table 4 below lists the name, type of measure, source, and number of times administered, followed by a detailed description of each.

Table 4. *Overview of Measures Used in the Exploratory Case Study*

Name of Measure	Type/Reliability	Source	# of Times Administered
Pedagogical knowledge (PK)	6 quantitative questions/ Cronbach's alpha = 0.85	Banas & York (2014)	Week 1, 2, 3
Technological pedagogical knowledge (TPK)	4 quantitative questions/Cronbach's alpha = 0.84	Banas & York (2014)	Week 1, 2, 3
Teaching efficacy	12 quantitative questions/ Cronbach's alpha = 0.91	Tschannen-Moran & Hoy (2001)	Week 1, 2, 3
Teacher resiliency	25 quantitative questions/Cronbach's alpha = 0.91	Wagnild & Young (1993)	Week 1, 2, 3
Post-professional development interview questions	3 quantitative questions	Developed by author	Week 1, 2, 3
Response to general scenario question in the case study	1 qualitative question	Developed by author	Week 1, 3
Learning analytics knowledge questions (pretest)	20 multiple-choice and blank-filling questions	Developed by author	Week 1
Learning analytics knowledge questions (posttest)	21 multiple-choice and blank-filling questions	Developed by author	Week 3

Survey Packet: PK, TPK, Teaching Efficacy, Teacher Resiliency

The survey packet consisted of several surveys (i.e., PK, TPK, teaching efficacy, and teacher resiliency) that were administered throughout the 3-week learning analytics professional development (see Table 4). The Technological & Pedagogical Knowledge (TPK) Questionnaire consists of four questions that measure how teachers use technologies in their teaching and how they see technology as a way to change instruction. TPK is the same measure administered in the learning analytics survey study (please refer to the Measures section in Chapter III). To estimate the effect of the professional development on novice teachers' general pedagogical knowledge, another pedagogical knowledge (PK) from Banas and York (2014) was also incorporated. Banas and York's PK measure came from the original PK measure developed by Schmidt et al. (2009). The only difference in the Banas and York version was that they removed one question (*"I know how to organize and maintain classroom management"*) from the original measure because classroom management was not an integral part for the teacher training in their study. Banas and York's PK measure was also administered in this case study because classroom management was also not the focus of the learning analytics professional development. Example questions from the PK measure included: *"I can assess student performance in the classroom"* and *"I can adapt my teaching style to different learners."* For both PK and TPK measures, participants were asked to respond to these statements using a 7-point Likert scale, where 1 indicated *disagree* and 7 indicated *agree*. The PK and TPK measures have been validated to have high reliability where Cronbach's alpha for PK = 0.85 (6 questions) and Cronbach's alpha for TPK = 0.84 (4 questions).

Teaching Efficacy is the same questionnaire administered in the learning analytics survey study (please refer to the Measures section in Chapter III). This questionnaire developed by Tschannen-Moran and Hoy (2001) measures teacher's efficacy and confidence in instructional practices and student engagement and has a high reliability of Cronbach's alpha = .91 (12 questions). An example question in this measure is *"To what extent can you use a variety of assessment strategies?"* For each question in this measure, participants were asked to respond on a 9-point Likert scale where 1 indicated *Nothing* and 9 indicated *A great deal.*

The new measure added to this case study was the Teacher Resiliency questionnaire developed by Wagnild and Young (1993) as a 25-item Resilience Scale (RS). It is a widely used resilience measure for research with teachers. Pretsch, Flunger, and Schmitt (2012) adopted Wagnild and Young's measure and found teacher resiliency could predict their well-being, which included their general health perception, job satisfaction, exhaustion, and physical illness. The reliability of this teacher resiliency questionnaire is high, with Cronbach's alpha at 0.91 (Wagnild & Young, 1993). In Pretsch et al.'s (2012) study that focused primarily on teachers, Cronbach's alpha was 0.85. Example questions in this measure included *"I am able to depend on myself more than anyone else"* and *"My belief in myself gets me through hard times."* This measure was conducted with a 7-point Likert scale, where on that scale 1 indicated *disagree* and 7 indicated *agree*.

It is important to note the timing of when the survey packet (PK, TPK, teaching efficacy, teacher resiliency) was administered. For the first week, all these measures were administered before the tutorial in order to set a benchmark. For the second and third weeks, these measures were implemented after the learning analytics tutorial session. The scores of these measures from different weeks were calculated and compared to examine the effects of the learning analytics professional development throughout the 3 weeks.

Interview Questions

Three interview questions were administered after each tutorial to elicit the participants' feedback on their learning experience and how participants perceived the weekly tutorial in terms of its relevance to their own teaching, the importance of the tutorial topic, and how they see themselves applying the weekly learning analytics topic to their teaching. These three interview questions were:

1. *Can you mention three things you think most relevant to your teaching about today's tutorial?*
2. *Based on what you learn today about (weekly subject names), can you give me an example about how you will use it in your teaching?*
3. *How important is this week's tutorial content to your teaching and why?*

General Scenario Question from the Case Study

For the first and last weeks (i.e., third week) of the learning analytics professional development session, participants were asked to respond to a scenario question after reviewing the teaching scenario about their fictional colleague, Megan, and her teaching scenario. The participants received the following prompt from the facilitator:

> *You have read about Megan's teaching scenario. Now Megan wants to know how you find out your teaching skills and students' learning outcomes. How would you respond to her?*

Participants were asked to respond freely to this question on two occasions (Week 1 and Week 3) to see how their response might change before and after experiencing the learning analytics professional development.

Learning Analytics Knowledge and Skill Questions

In the first week as a pretest and the last week as a posttest, a set of learning analytics knowledge and skill questions was administered to measure the participants' learning gains from the three tutorials (see Table 4). The questions from the pretest and posttest covered the 3-week learning analytic tutorial content. The questions were slightly rephrased from pretest to posttest. Some questions were the same, but asked as a two-part question, covering the same content. Participants' responses to these questions included multiple-choices, explanation for multiple-choice questions, blank-filling questions, and the calculation process for those blank-filling questions. Some questions asked for explanations to ensure that multiple-choice questions were not answered correctly by chance and participants truly understood the statistical concept. Because some questions were changed from a single question to a two-part question, it may appear there was a different total number of questions from pretest to posttest, but the tests placed equal weight on each question, totaling to the same 54 points. Originally, two new additional questions on the posttest were later removed due to redundancy and limited time.

There were three types of questions on both the pretest and posttest, which were categorized as (1) basic, (2) inference, or (3) applied and increased in difficulty levels. For example, for concepts on mean and median, a basic-level question appeared as follows in Figure 8.

Figure 8. Example of Basic-level Learning Analytics Question

1.1 To get a sense of students' average performance, you can calculate median. Given two student groups' scores below, please write down your calculation process and the median for each group below:

Group 1 scores: (70, 50, 97, 83)
Group 2 scores: (100, 40, 55, 80)

Please put your calculation process here:

Group 1 median: ______________
Group 2 median: ______________

For all learning analytics questions in the pretest and posttest, to answer a basic-level question correctly required participants to recall the steps to compute a numeric value. In the above example, participants needed to remember the steps to compute the median value for the two given number lists (i.e., sort numbers in each list and retrieve the middle number).

The second level of the learning analytics knowledge question was inference questions. For inference-level questions, participants needed to think more critically, where interpretation may need to be drawn from multiple sources of information to get an answer. For example, in the inference-level question below, participants needed to think critically about how to sort each number list after adding the new number 88 and how to get the median when the total number in each list was an even number.[1]

[1] The correct steps to get a median value when there is an even number of numbers in a list is: (1) sort all the numbers based on the values of the number, (2) take the mean of the two middle numbers. For instance, for the number list (1,2,3,4), the median will be (2+3)/2=2.5.

Figure 9. Example of Inference-level Learning Analytics Question

1.4 If there is a new score 88 to be added into each of the two group scores, what is the new median for each group?

Group 1 scores: (60, 77, 55, 97, 81)
Group 2 scores: (88, 42, 30, 95, 100)

Please put your calculation process here:

Group 1 median: _____________
Group 2 median: _____________

The third type of question was the applied questions. The applied questions tested participants' ability to synthesize their basic- and inference-level knowledge and use it in a practical scenario. Not only did participants need to know the concept and be able to perform basic computation, but they also needed to be able to compare different answer options in a near-reality scenario. An example application-level question is shown below in Figure 10.

Figure 10. Example of Applied-level Learning Analytics Question

1.6 Suppose you have four student scores on a math quiz as shown below, will you choose mean or median to better represent the center of these student scores? (select one answer)
Students' math quiz scores: (10, 15, 20, 90)

◯ 1. Mean
◯ 2. Median
◯ 3. I am not sure

Please explain your answer:

For this applied question, participants needed to: (1) know the basic definition of mean and median; (2) identify steps to compute mean and median values of the same number list; (3) compare mean and median value; (4) think critically if mean or median can better represent the center of students' scores in a real teaching setting; and (5) write down their reasoning to explain their answer. Thus, applied questions could be seen as the integration of the basic- and inference-level hands-on questions in real life that extended learning analytics knowledge from the conceptual to the pedagogical level.

Results of the Case Study

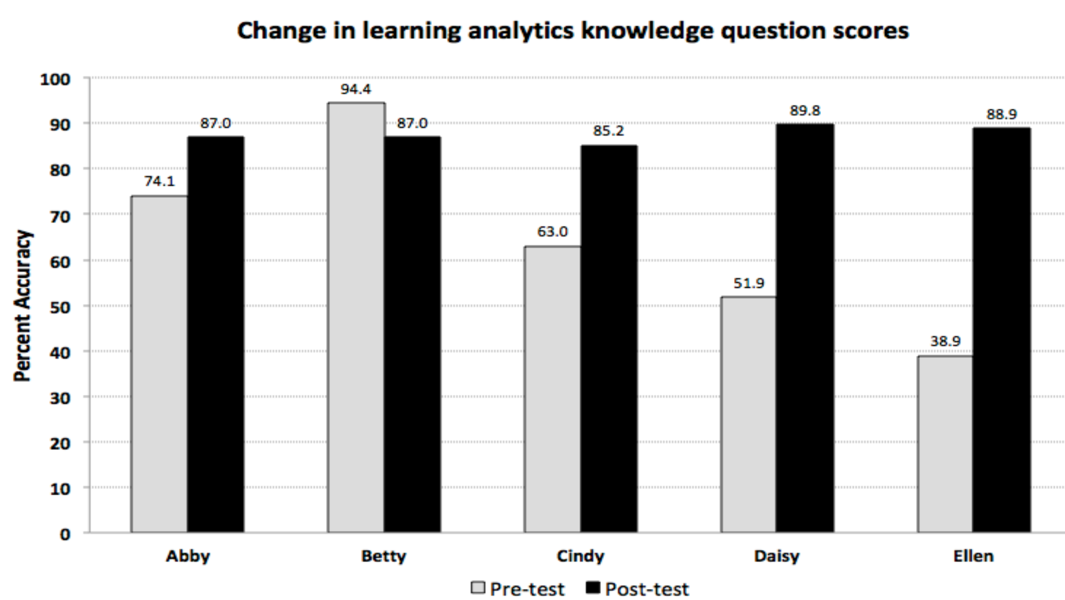
This section describes the results from the learning analytics professional development in this case study. I begin by providing the results of the intervention at the group level that included all five participants (i.e., Abby, Betty, Cindy, Daisy, and Ellen). I then take a closer look at each participant individually with regards to their knowledge from the intervention, TPK, PK, teaching efficacy, and teaching resiliency.

Sub-question 1. At the Group Level, Can Professional Development in Learning Analytics Assist Novice Teachers in Developing Skills to Assess Teaching Practices and Student Performance?

Learning gains after the 3-week learning analytics professional development sessions. There was a total of 32 questions with a total score of 54 points in both pretest and posttest. For the convenience of data analysis, participants' raw scores were converted into an accuracy percentage. For instance, if a participant scored 40 out of 54 total points, then her accuracy percentage score was 40/54 x 100 = 74.1 points. The same accuracy percentage conversion was applied to participants' posttest scores as well.

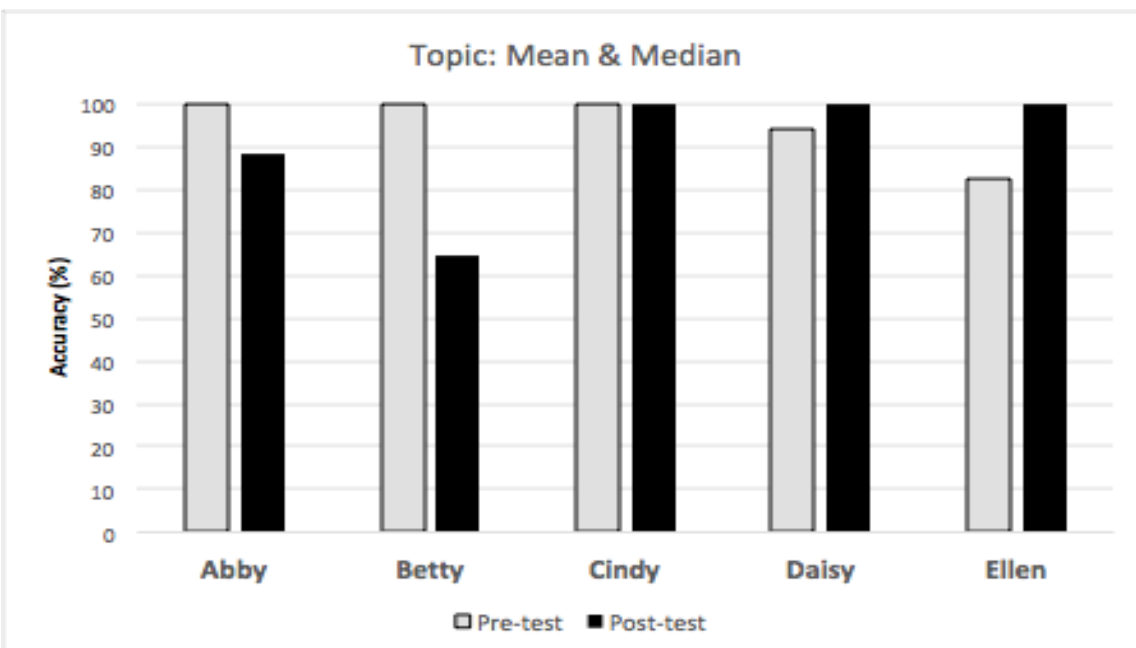
The results showed that after 3 weeks of the learning analytics professional development, nearly all participants had increased their learning analytics knowledge with the exception of Betty (see Figure 11). For the first novice teacher, Abby, her learning analytics knowledge score increased from 74.1 to 87 points. The second novice teacher, Betty, was the only participant who showed a slight decline in the score after the learning analytics professional development; her score went from 94.4 to 87 points. Despite the slight score decline, Betty's pretest and posttest scores were still the highest among all participants. The third teacher, Cindy, showed a significant score increase from 63 to 85.2 points. Similarly, Daisy's score also increased significantly from 51.9 to 89.8 points. The last novice teacher, Ellen, demonstrated the largest growth in the learning analytics knowledge score: Her score increased from 38.9 to 88.9 points between the pretest and posttest.

Figure 11. Change in Learning Analytics Knowledge after Learning Analytics Professional Development for All Participants



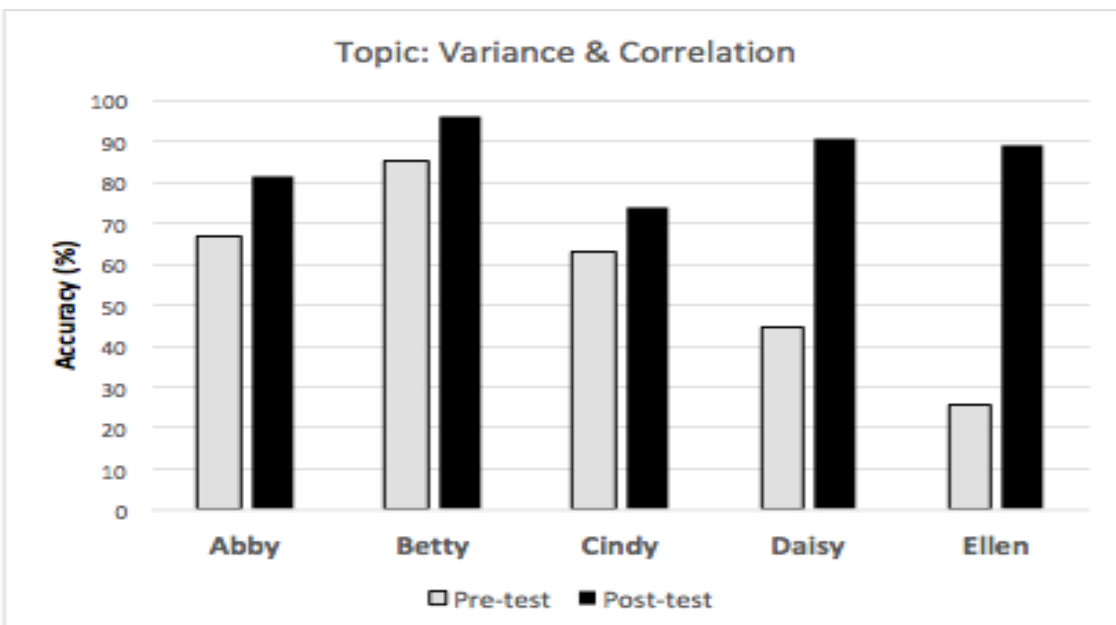
Learning analytics knowledge increase by tutorial topic. When I further divided pretest and posttest questions based on learning analytics topics and compared the accuracy percentage for participants' question responses, the results showed some interesting patterns. For the topic of mean and median in statistics (see Figure 12), it was clear that all five participants attained a high score in the pretest (i.e., higher than 80 points). Interestingly, in the posttest, the first two teachers, *Abby* and Betty, both showed a decline in their scores. *Betty*'s accuracy score in the posttest especially had decreased by more than 30 points on the mean and median subject. The third teacher, *Cindy*, maintained a full score on this topic in both pretest and posttest. The other two teachers, *Daisy* and *Ellen*, showed improvement in their scores between pretest and posttest.

Figure 12. Change in Learning Analytics Knowledge by Subject: Mean and Median



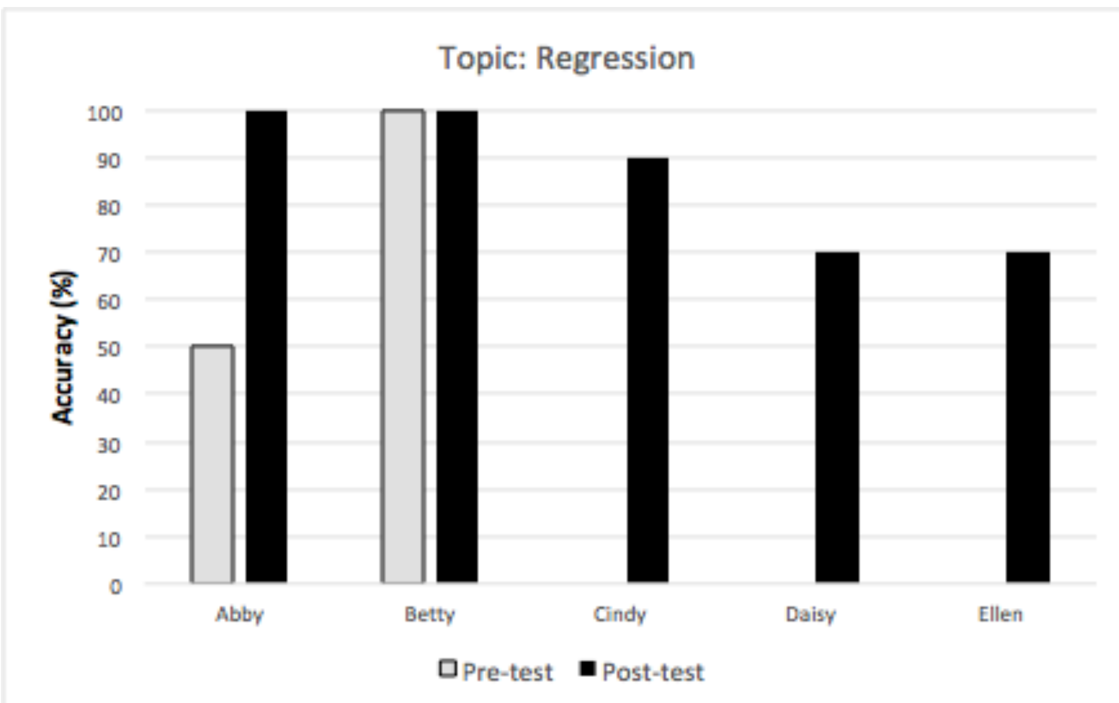
With regard to the topics of variance and correlation, all five participants showed improvement in their scores between pretest and posttest. The first three teachers, *Abby*, *Betty*, and *Cindy*, increased around 10 points between pretest and posttest. For *Daisy* and *Ellen*, their scores showed a dramatic change. *Daisy* increased around 45 points, while *Ellen* improved around 55 points between their pretest and posttest on the subject of variance and correlation. All the participants except for *Cindy* were able to attain 80% accuracy in their posttest scores. *Cindy's* posttest score was a bit over 70% (see Figure 13).

Figure 13. Change in Learning Analytics Knowledge by Subject: Variance and Correlation



Regarding the last learning analytics topic of regression, all five participants showed improvement in their scores between pretest and posttest, with the exception of *Betty*, who maintained a full score between pretest and posttest. In general, participants showed the largest score improvement on this topic (i.e., regression), compared to other previous topics (i.e., mean, median, variance, correlation). *Abby's* score improved by 50 points after the professional development. The other three teachers, *Cindy*, *Daisy*, and *Ellen*, showed tremendous increase in their scores in the posttest by 90, 70, and 70 points, respectively. The results showed that regression was the learning analytics knowledge in which participants showed the largest improvement through their pretest and posttest score comparison.

Figure 14. Change in Learning Analytics Knowledge by Subject: Regression

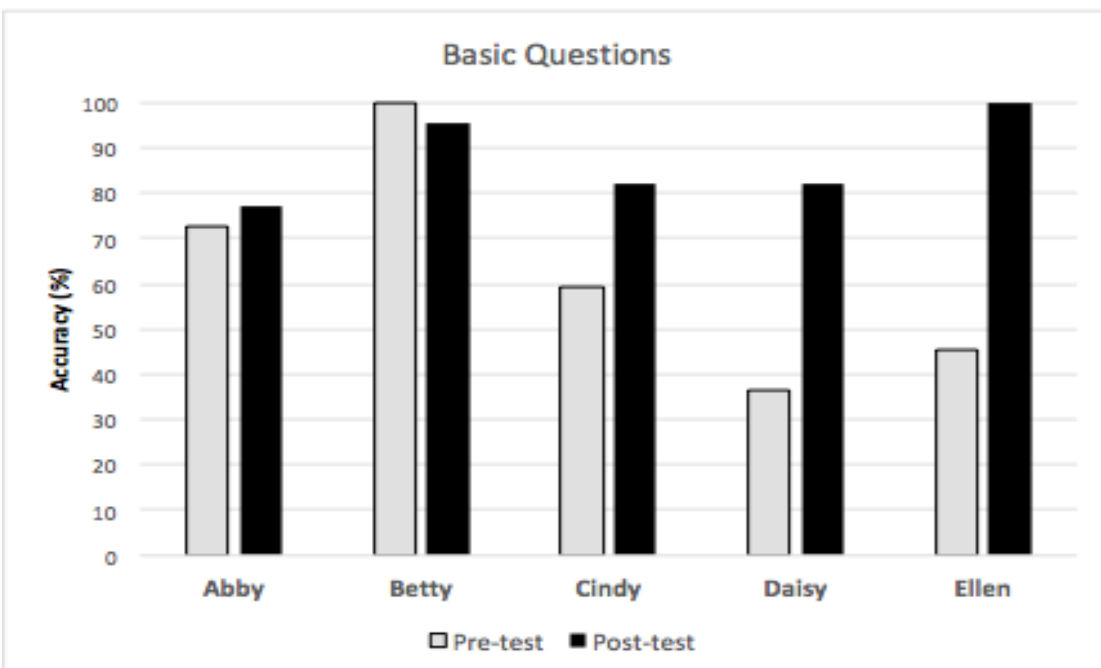


Learning analytics knowledge increase by question levels. There were three levels of learning analytics knowledge questions in both pretest and posttest: basic, inference, and applied. Each tutorial topic had these three levels of questions and the number of each level of questions was similar. Some interesting results emerged when I broke down the pretest and posttest scores of learning analytics knowledge questions based on the three types of questions.

For the basic-level questions, all five participants showed improvement except for the second teacher, *Betty*, in terms of their pretest and posttest scores (see Figure 15). *Betty* was the only teacher who showed a slight score decline around five points of all participants. Despite her score decline, however, *Betty* still had the highest score in pretest and posttest.

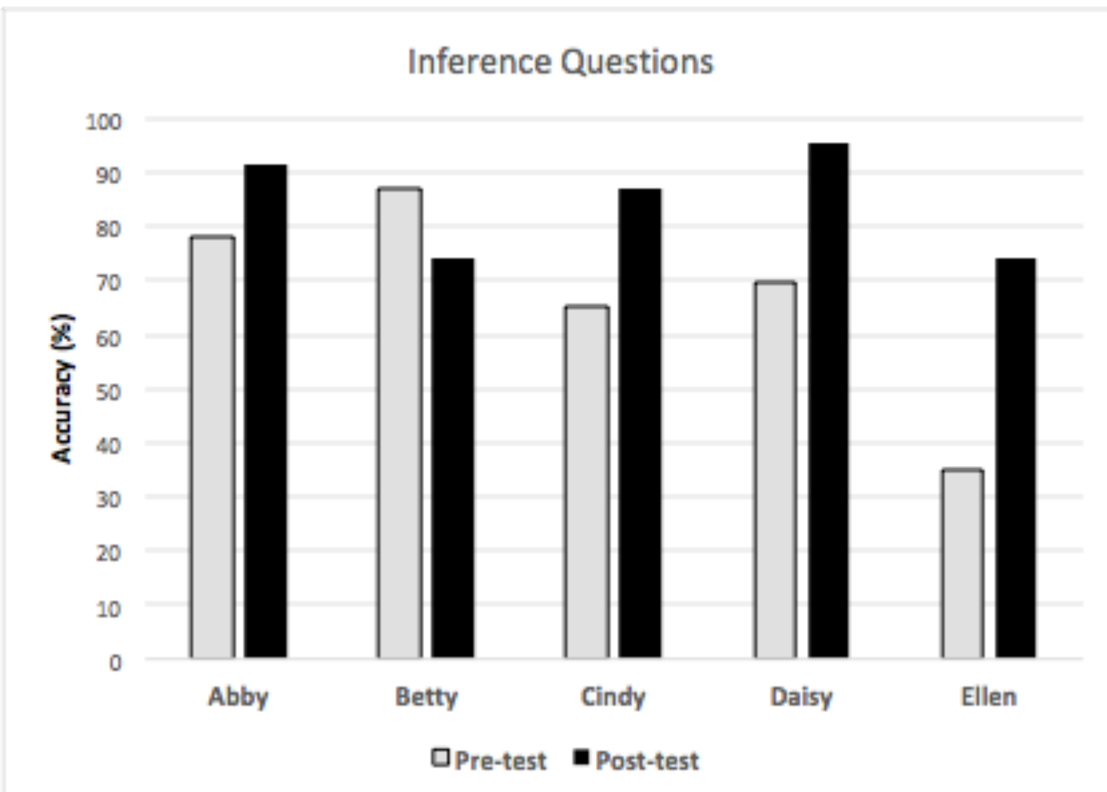
The improvement of the score of the first teacher, *Abby*, was smaller than the other three teachers: *Cindy*, *Daisy*, and *Ellen*. Both *Daisy* and *Ellen* demonstrated a large score growth. *Daisy* improved around 45 points and *Ellen* increased 55 points between pretest and posttest on the set of basic questions.

Figure 15. Change in Learning Analytics Knowledge by Question Type: Basic



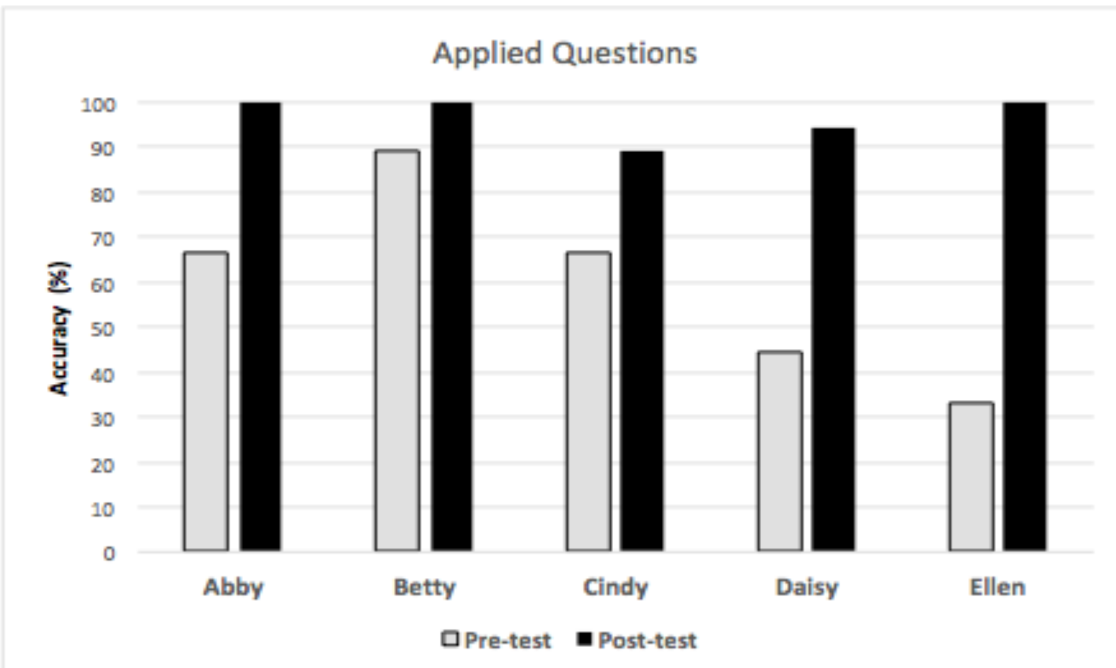
With regards to the Inference questions (see Figure 160, a similar pattern of participants' scores appeared as in the Basic question. All participants but *Betty* showed an increase in their scores between pretest and posttest. There was a score decline of about 13 points for *Betty*, which made her score the lowest of all (on a par with *Ellen*). For *Abby*, there was a small improvement of around 13 points in her posttest score. *Cindy* and *Daisy* improved by 22 and 26 points, respectively. Finally, *Ellen* showed the largest improvement of all: around 39.1 points, from 34.8 to 73.9 points between the pretest and posttest.

Figure 16. Change in Learning Analytics Knowledge by Question Type: Inference



For Applied questions, all five participants exhibited an improvement in their scores between pretest and posttest. *Abby*, *Betty*, and *Ellen* achieved a perfect full posttest score of 100. *Ellen* showed the biggest improvement with 66.7 points, while *Abby*, *Cindy,* and *Daisy* also showed some significant improvement by about 33, 22, and 50 points, respectively. Although *Betty* did not show a large improvement comparatively, her pretest and posttest scores remained the highest among all participants.

Figure 17. Change in Learning Analytics Knowledge by Question Type: Applied



Sub-question 2. At the Group Level, How Does Professional Development in Learning Analytics Influence Novice Teachers' Pedagogical Knowledge (PK) and Technological Pedagogical Knowledge (TPK), Teaching Efficacy, and Teacher Resiliency?

In general, there was an increase in the average PK, TPK, and teacher resiliency combining all five novice teachers after the intervention. The group average PKs throughout the 3 weeks were 5.5, 5.5, and 5.9 points (7-point Likert scale, with 4 indicating *no opinion*). The group average TPKs increased from 5.1 to 5.6 and 6.2 points throughout the 3 weeks (7-point Likert scale, with 4 indicating *no opinion*). Finally, for the group average of teacher resiliency, the average score increased from 5.1 to 5.5 and 5.7 points throughout the 3 weeks (7-point Likert scale, with 4 indicating *no opinion*). The change in the group average of teaching efficacy was minimum. The average teaching efficacy scores throughout the 3 weeks were 5.9, 6.1, and 6 points (9-point Likert scale, with 5 indicating *no opinion*).

Figure 18. Average Change in PK, TPK, Teacher Resiliency (as a Group)

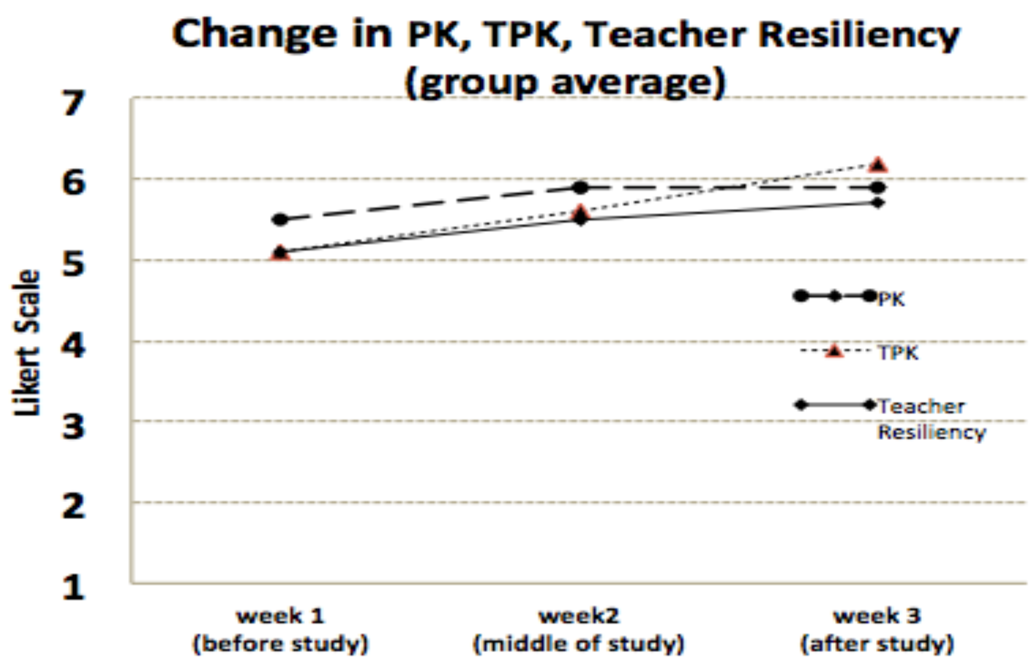
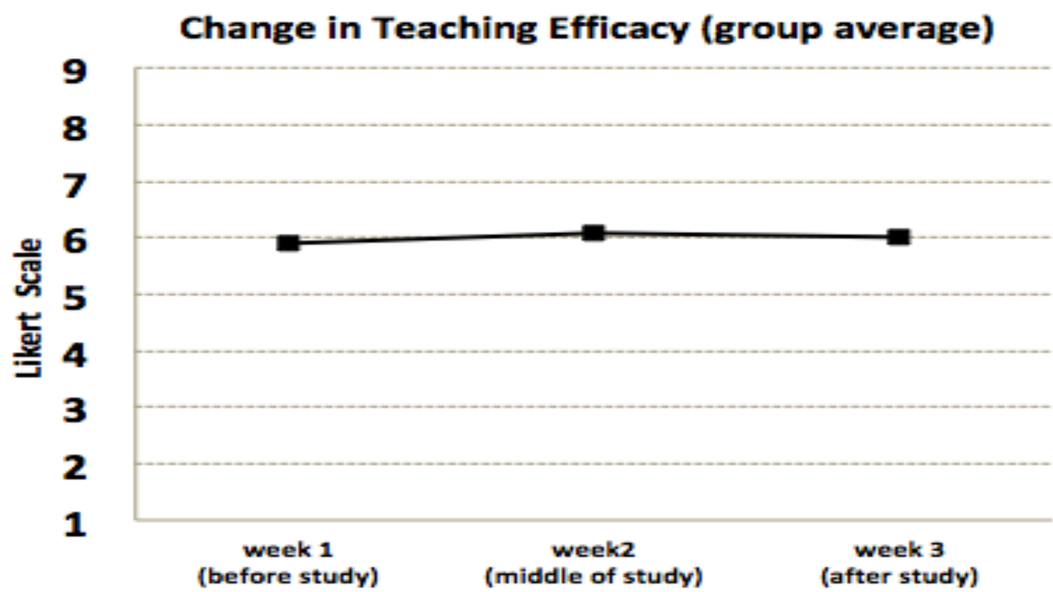
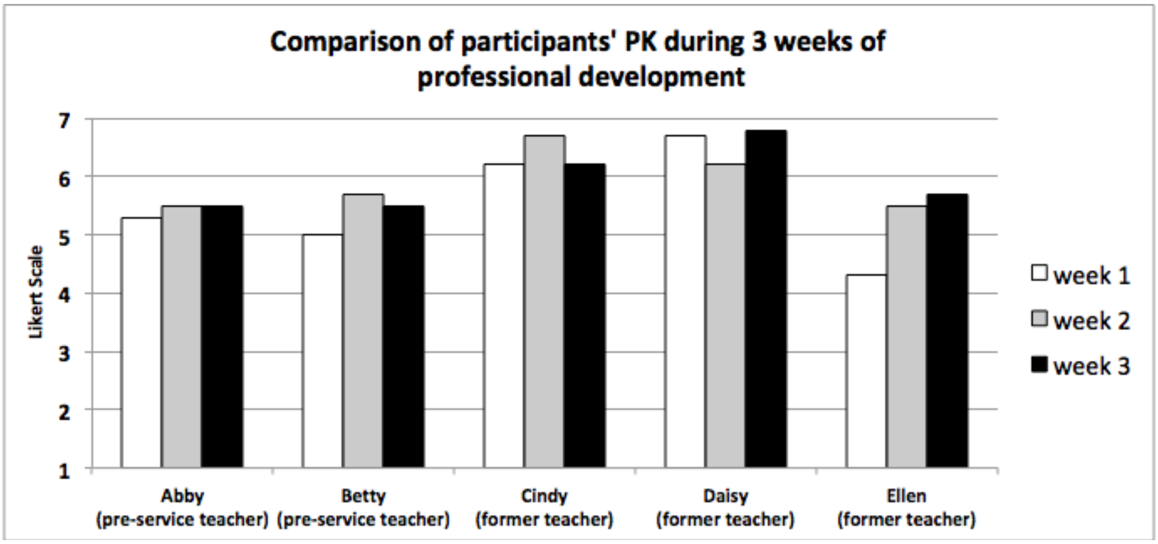


Figure 19. Average Change in PK, TPK, Teacher Efficacy (as a Group)



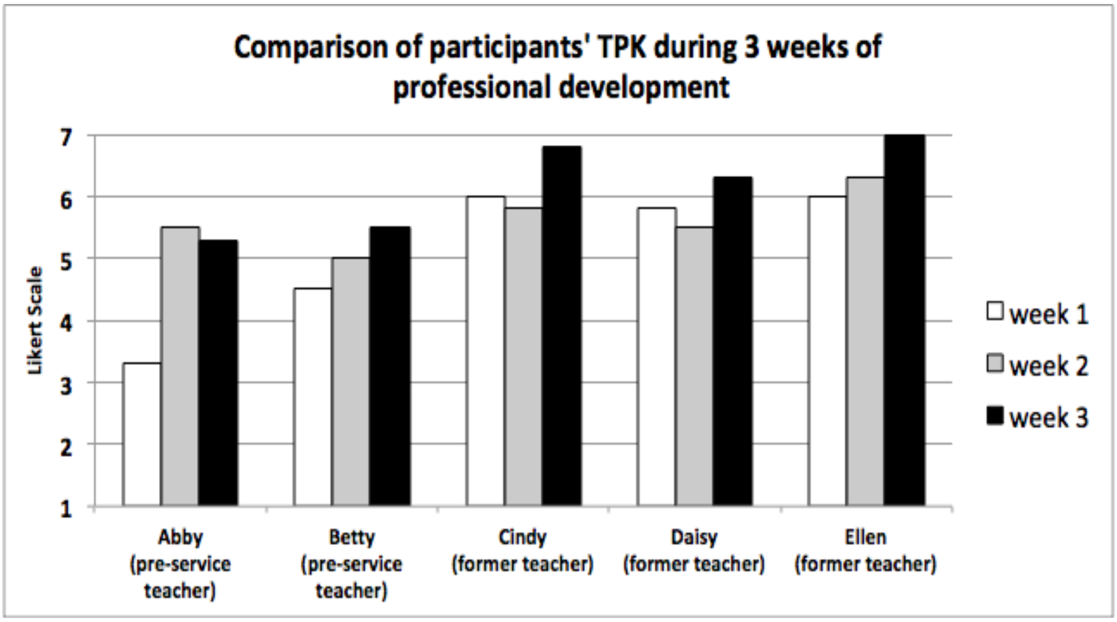
Another important result emerged when I compared participants' PK based on their levels of teaching experience (see Figure 20). The three former teachers (i.e., *Cindy*, *Daisy*, and *Ellen*) had more prior teaching experience than the two other preservice teachers (i.e., *Abby* and *Betty*). When I compared former teachers' and preservice teachers' PK as two groups, the former teachers' PK scores were higher than the preservice teachers' PK scores in the third week's posttest. For the pretest in the first week, except for one former teacher, *Ellen*, the other two former teachers' PK scores were also higher than those of the two preservice teachers.

Figure 20. Comparison of PK Between Preservice and In-service Teachers



The results showed that the change in participants' TPK could potentially relate to their experience of using LMS and learning analytics functions. Two preservice teachers (i.e., *Abby* and *Betty*) and one former teacher, *Ellen*, increased their TPK relatively more than the two other teachers (i.e., *Cindy* and *Daisy*) between the first and third weeks (see Figure 21). *Abby*, *Betty,* and *Cindy* increased their TPK by 2, 1, 1 point(s) on a 7-point Likert scale, respectively. In contrast, *Cindy* and *Daisy* increased only 0.8 and 0.5 points, respectively, on the same TPK measure scale. Although there might be other factors that could cause this difference, one reason could be the different levels of experience in using LMS learning analytics. *Abby*, *Betty*, and *Ellen*, who showed a higher increase in TPK, hade more years of experience using different LMS or learning analytics functions, compared to the two other teachers.

Figure 21. Comparison of TPK Between Participants



Up until this point, I have reviewed the results of the case study at the group level. The next section takes a closer look at all participants in the case study. The two research questions to be answered at the individual level are:

Sub-question 1 (at individual level): Can professional development in learning analytics assist each individual novice teacher in developing skills to assess teaching practices and student performance, and develop their confidence in using learning analytics in teaching?

Sub-question 2 (at individual level). How does professional development in learning analytics influence each novice teacher's pedagogical knowledge (PK) and technological pedagogical knowledge (TPK), teaching efficacy, teacher resiliency, and their intentions to use learning analytics in their teaching?

As a recap, I include each participant's profile along with her learning analytics knowledge, and perceptions of her PK, TPK, teaching efficacy, and teacher resiliency, as a result of the 3-week intervention. Evidence for any changes in each participant's confidence about learning analytics and her intention to use learning analytics is also included.

Profile and Learning Progress Description for Individual Teachers in the Case Study

Abby. *Abby* was a 23-year-old preservice teacher in her first-year math education program. She had no formal teaching experience at school in the past. She planned to teach high school math after she graduates. She shared that she had very competent quantitative skills as she used to work as a statistician. She had experience of using LMS functions as a student, but never used LMS or any learning analytics in teaching before. Before the professional development started, all participants were asked the question *"How comfortable do you feel about helping your colleagues with their statistical questions?"* in order for me to get an impression of how participants felt about their statistical skills. On a scale from 1 to 5, with 1 indicating *not comfortable* and 5 *very comfortable*, *Abby*'s answer was 3 (*no opinion*).

For the learning analytics knowledge question, *Abby* improved around 13 points between pretest and posttest. In general, when breaking down *Abby*'s scores based on different learning analytics tutorial topics, her pretest and posttest scores showed that she was very familiar with the topic of mean and median and also had an average understanding of the topics of variance and correlation. *Abby* did not seem to have a solid grasp of regression based on her pretest score on the regression questions (from 50 points), but she showed a large improvement on the regression questions in the posttest (50-point increase and achieved a full score). *Abby* also showed an improvement in the score for variance and correlation (15-point increase). Interestingly, *Abby* did slightly worse for the mean and median questions, but still attained a high score in the posttest (88.2 points).

When examining *Abby*'s PK, TPK, teaching efficacy, and teacher resiliency (see Figure 22), it was found that *Abby* improved her TPK from the first week to the third week's learning analytics professional development (3.3 to 5.5 point, with 4 being the middle point indicating *no opinion*). Her improvement of TPK resonated with her feedback on the interview questions. When asked about the relevance and importance of each week's tutorial topic, *Abby*'s response focused mostly on her gain of technical skills to use Excel. For instance, she shared the following:

> *I think reviewing basic Excel skill to operate these statistical concepts help[s] me brush up on the statistical knowledge of mean and median, although I am very familiar with these statistical concepts already, and doing so give me more confidence. (Week 1: mean and median)*

Figure 22. Change in *Abby*'s PK and TPK

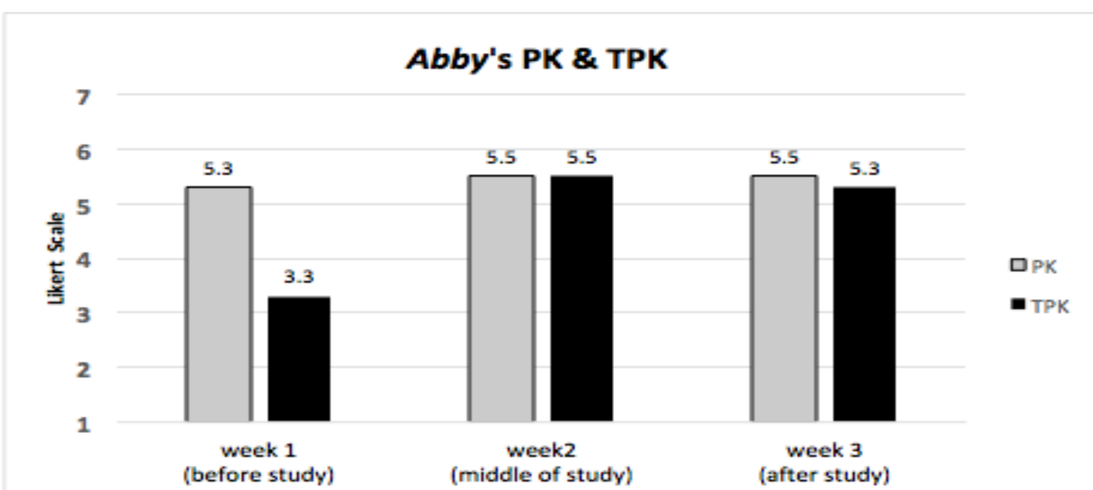


Figure 23. Change in *Abby*'s Teaching Efficacy

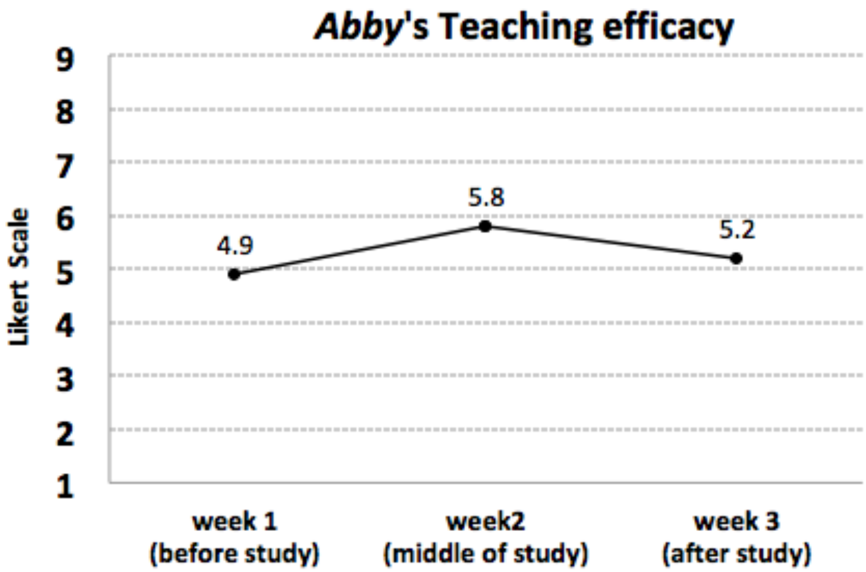
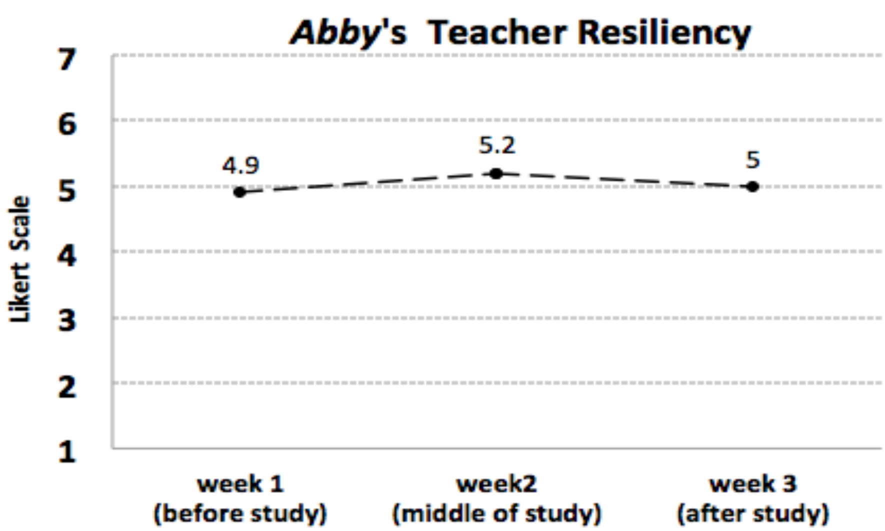


Figure 24. Change in *Abby*'s Teacher Resiliency



For topics with which *Abby* was less familiar, such as variance and correlation, she expressed that going through the activities in this tutorial helped her review these concepts with hands-on practice.

> *I used to be a statistician, and it is very helpful for me to go through this tutorial to reconsolidate these concepts. Also, it is useful for me to know how to run correlation analysis in Excel. I didn't know how to do this before this tutorial….* (Week 2: variance and correlation)

Abby's PK score went from 5.3 to 5.5 points on a 7-point Likert scale between the first and third weeks. While not a large increase, the scores showed a sign that she remained with a moderate-to-positive perception of her PK. Similarly, her teaching efficacy score did not change much after the professional development (4.9 to 5.2 points, with 5 being the middle point indicating *no opinion*) on a 9-point Likert scale. Yet the results showed the direction of a positive perception of her teaching efficacy. Interestingly, *Abby* attained the highest teaching efficacy score in the second week (5.8 points), but the score dropped at the end of the third week. This score decline could be due to her unfamiliarity with the topic of regression. Although she believed she was familiar with regression in statistics, her low pretest score on regression questions and her response during the interview might have shown that she may not have been very knowledgeable of regression analysis. She shared:

> *Reviewing the concepts of coefficients and p-value for regression has given me more confidence as I was re-consolidating these knowledge. It is useful to look into and learn together with the facilitator about the meaning of coefficients in regression. Although I used to be a statistician, this tutorial has really helped me to know how to explain these coefficients in a more understandable way especially to Megan in the case study. Now I know how to explain these to other teachers without statistical background. The last thing is knowing how to read and explain a regression table output. Being able to know how to produce and read a big regression statistical table in the Excel really helps me to review because I didn't get much opportunity before.* (Week 3: regression)

It is unusual for someone who has worked as a statistician not to know how to read a statistical table for regression in statistics, even in Excel. Therefore, it is likely that after the third week's tutorial, which focused on the topic of regression, *Abby* encountered some "reality check" about her knowledge of regression and realized she did not have sufficient knowledge of regression analysis. This wake-up moment could potentially hurt her confidence and thus reduce her teaching efficacy. Although a similar pattern also emerged in *Abby's* TPK and teacher resiliency, where her scores dropped slightly from the second to the third week, these declines were very minimal, and it was less certain whether these declines were associated with the same reason about her learning experience with regression in the third week. *Abby*'s teacher resiliency did not change much after the intervention. Her teaching resiliency score remained around 5 points on a 7-point Likert scale (with 4 being the middle point indicating *no opinion*). This result might imply that *Abby* had maintained a slightly positive perception of her teacher resiliency. It is important to point out that despite some of *Abby*'s changes on the measure in this study being obvious, these quantitative results are presented in the manner of descriptive statistics rather than inferential statistics. In other words, the changes in Abby's outcome metrics are not meant to make any statistical generalization or inference for a larger teacher population. Moving forward, the same caveat will also apply to the other participants in this case study. During the interview, *Abby* was also asked how she planned to apply the knowledge she learned from the professional development to her teaching, and she gave the following feedback for each week's tutorial topic:

> *As a teacher, it is very important to know how to use mean or median at the right time. If students' scores deviate too much from the mean or median, it would be something that a teacher like me should be concerned about.* (Week 1: mean and median)

> *I would try to do the same thing like what we practiced in this tutorial. I will plug in students' scores and try to see the correlation between different learning*

> *activities to see if I can find some clues about how different activities relate to each other, and how they each relate to the exam in order to improve students' learning.* (Week 2: variance and correlation)

> *I would say regression is very useful in terms of predicting students' performance. By seeing the regression coefficients, I would know which learning activities are important to students. As a teacher, sometimes I am not aware of the importance of each activity when I am designing them, so this is a good way to trace which assignment or quiz has the most impact on students' exams.* (Week 3: regression)

Before the learning analytics tutorials began in the first week, all five participants read the teaching scenario about their fictitious teacher colleague, Megan, and her teaching scenario. After reading the teaching scenario, all participants, including *Abby*, were asked a scenario question: *"You have read about Megan's teaching scenario. Now Megan wants to know how you find out your teaching skills and students' learning outcomes. How would you respond to her?"* This scenario was designed to measure the participants' confidence, knowledge, and intention to integrate learning analytics in teaching. Before the tutorials, *Abby*'s response to this question was as follows:

> *I would say at this point since my teaching experience is very limited. I will use self-reflection on my teaching and having feedback from other people that observe my teaching. Also, I will also use my students' feedback.* (Week 1: before the first learning analytic tutorial)

After the 3-week learning analytics tutorial at the end of the professional development, *Abby*'s answer to the scenario question did not include anything directly about learning analytics, or specific knowledge or skills introduced in the tutorials. However, she did mention a new approach which was to observe other people's teaching practices. It is possible that *Abby* became inspired by the teaching scenario and the learning analytics activities in the professional development when she had to evaluate another teacher's (i.e., Megan) teaching outcomes.

> *I think everyone has their teaching styles and preferences. And I think I can benefit from observing others' teaching and use other people's good teaching practices in my own teaching. It took me a long time to adjust my teaching so I can get to a level of feeling good enough to teach my students. A lot of practice will help. To evaluate my own teaching, I would see the reactions from my students in the classroom. For example, if they are falling asleep or leaving the classroom. I will also focus on the students' feedback in the comment section in my teaching evaluation.* (Week 3: after the last learning analytics tutorial)

Betty. *Betty* was a second-year preservice teacher in a math education program. She was 22 years old and planned to teach middle school or high school math after graduating from her teacher education program. She did not have any former teaching experience as a full-time teacher at a school. She has used different LMS such as Canvas and Class Dojo as a student, but never as a teacher, nor has she ever used any learning analytics tools as a teacher. *Betty* was confident about her statistical knowledge and skills. When asked the question *"How comfortable do you feel about helping your colleagues with their statistical questions?"* before the tutorials started, *Betty*'s answer was 5, *"very comfortable,"* on a scale from 1 to 5, where 1 indicated *"not comfortable"* and 5 indicated *"very comfortable."*

Betty was the only participant who showed a slight decline between the pretest and posttest scores of the learning analytics knowledge questions (5.7 points decrease). Despite this score decrease, her pretest (94.4 points) and posttest scores (87 points) were still the highest among all participants. When breaking down *Betty*'s scores based on different learning analytics tutorial topics, I found that *Betty*'s score decrease resulted from her responses to the mean and median questions in the posttest. A deeper review of her handwritten calculation process for those mean and median questions showed that she misunderstood a median question as a mean question and thus lost three points in the original posttest score. She answered the similar mean and median question correctly in the pretest and also demonstrated a slight improvement in her scores for the variance and correlation questions. Her scores for the regression analysis in both pretest and posttest were perfect full scores. Therefore, it could be inferred that *Betty*'s decline in the learning analytics knowledge question score was due mainly to her mistake of reading the instructions incorrectly for the mean and median questions in the posttest. Overall, *Betty*'s performance on the learning analytics knowledge questions was the highest among all participants. This result resonated with her confidence in her statistical knowledge that she expressed in the survey before the tutorials.

When examining *Betty*'s PK, TPK, teaching efficacy, and teacher resiliency (see Figure 25), the results showed that, overall, there was an incremental improvement on these outcome measures for her. Between the first and third weeks of the professional development, her PK increased from 5 to 5.5 on a 7-point Likert scale. Her TPK also rose from 4.5 to 5.5 on a 7-point Likert scale. For teaching efficacy, which was measured based on a 9-point Likert scale with 5 being *no opinion,* her score increased from 5.8 to 6.9. In the end, her teacher resiliency score increased slightly from 5.4 to 5.8 on a 7-point Likert scale, implying a positive perception of her teacher resiliency after the professional development.

Betty's growth in TPK and teaching efficacy was obvious. After the professional development, her perception of her own TPK and teaching efficacy turned from neutral (i.e., *no opinion*) to positive. From her interview responses, it is possible to see that the growth in her TPK and teaching efficacy may have come from the improvement in her technical skills to utilize Excel to perform learning analytics functions. For instance, here is how *Betty* felt about the first week's learning analytics tutorial for the topic of mean and median:

> *Since I am already familiar with the concepts of mean and median, I think knowing how to operate these concepts using Excel as a tool is really important to me. The Excel skills in today's tutorial are useful.* (Week 1: mean and median)

Also, for the second and third weeks, although *Betty* was already familiar with the weekly tutorial topics (i.e., variance, correlation, regression) based on her reactions during the tutorials and her performance on the pretest scores on those types of learning analytics knowledge questions, she found that this professional development extended her knowledge of those topics and helped her think of how to use them in her teaching. Here is some feedback from her when she was asked about the relevance and importance of the second and third weeks' tutorial to her:

> *Using correlation could help me know the underlying patterns. Another useful thing I would say is the correlation between students' academic performance and non-academic things, like students' average sleep hours in the tutorial. Something like tutoring time may correlates with students' performance at school and it will be interesting to know.* (Week 2: variance and correlation)

> *Regression model is the most important concept to me so far because it can predict students' performance. Also, by checking regression coefficients, I will know which learning activity contributes the most the exam and I can plan my teaching accordingly.* (Week 3: regression)

Meanwhile, by the second week, *Betty* had already started integrating and comparing the learning analytics knowledge she learned in the professional development and was thinking about the advantages and limitations of each learning analytics concept. Here is her feedback on the second and third weeks:

> *I think mean and median from the first week could only tell us how students perform, but correlation can give me ideas about how to help students improve their learning by giving them additional support.* (Week 2: variance and correlation)

> *Knowing how to use coefficients in a regression model is definitely helpful. In Week Two, I learned about correlation, but the correlation relationship probably can't provide strong evidence to tell us which variable contributes to which one so it is limited. But this week using regression can tell me about the causal relationship.* (Week 3: regression)

Overall, it seemed that *Betty*'s weekly growth in PK, TPK, and TPK could have been connected to her learning of how to utilize Excel to perform learning analytics concepts and put them into use for teaching design and teaching assessment.

Betty's teaching resiliency score did not change much after the professional development and remained around 5.5 points on a 7-point Likert scale, although there was a tendency of increase throughout those 3 weeks. This result implies that she exhibited a positive perception of her teacher resiliency.

Figure 25. Change in *Betty*'s PK and TPK

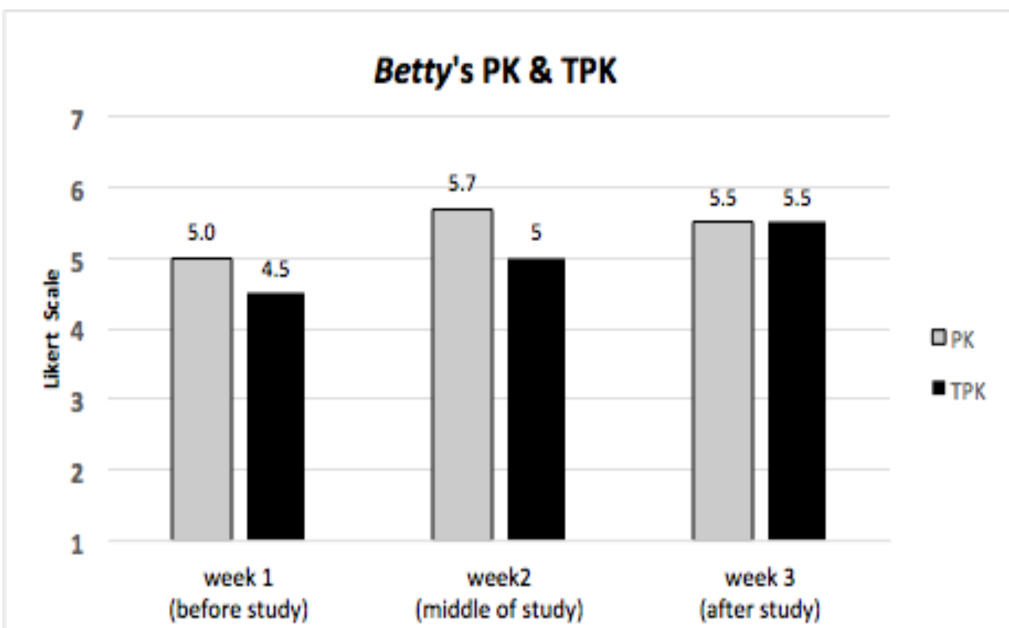


Figure 26. Change in *Betty*'s teaching efficacy

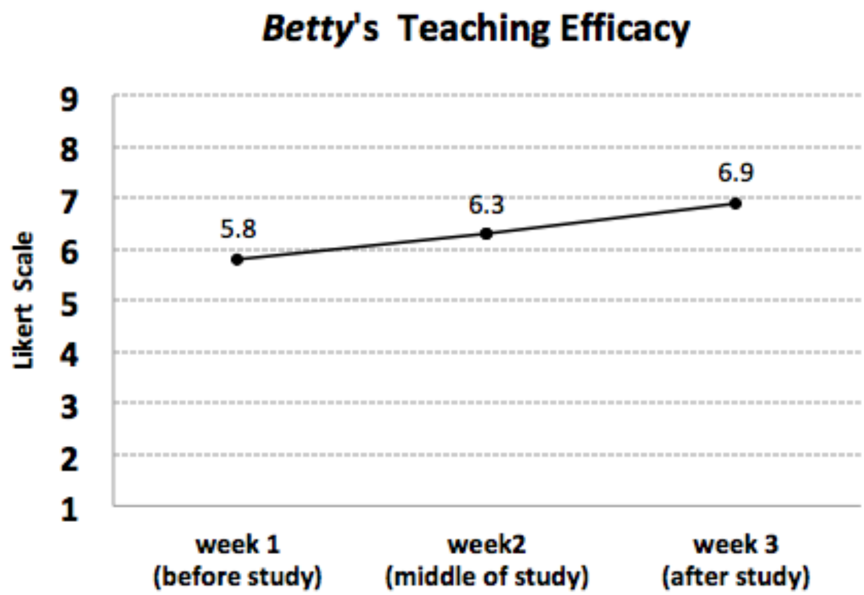
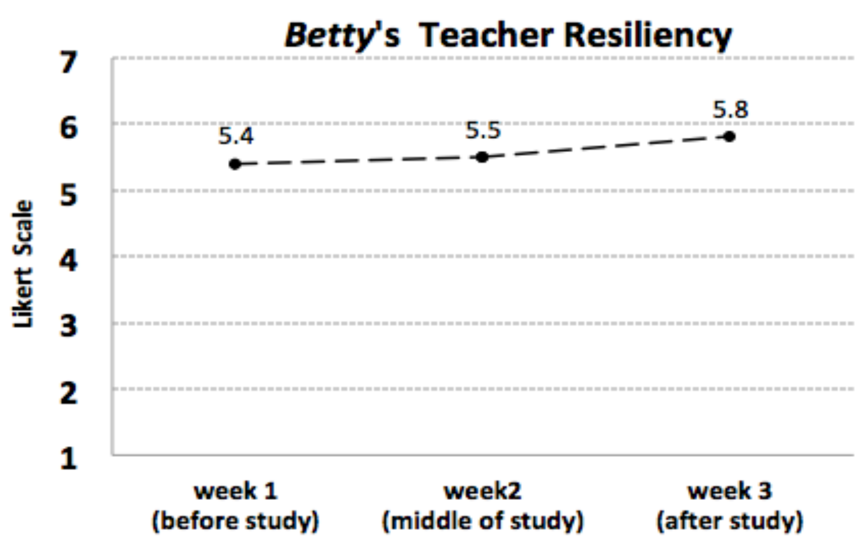


Figure 27. Change in *Betty*'s teacher resiliency



During the interview, *Betty* was also asked how she planned to apply the knowledge she learned from the professional development to her teaching. She shared some rather specific thoughts about her plans to use the variance, correlation, and regression knowledge to assess her own teaching and students' learning outcomes:

> *I will use variance to see my teaching performance. If there is high variance between students' performance, then it probably means there is something I can improve in my teaching. The second thing is to use correlation to see what correlate with the test score to see which learning activity is critical with regard to the test score.* (Week 2: variance and correlation)
>
> *Since I am doing student teaching for seventh graders and they will have the state test in April, if I could access students' scores from last year, I will input different scores on different activities in a regression model to use it to predict on the state test score. Doing so can tell me which activity is important with regard to preparation for the test. It can also help me predict which students are likely to pass the state test. All of these can help me to help my students to prepare for their tests.* (Week 3: regression)

Finally, before and after the 3-week learning analytics tutorials, *Betty* was asked to answer the scenario question *"How you find out your teaching skills and students' learning outcomes*" if Megan asked her. From her responses, it is possible to see that after the professional development, *Betty* developed confidence in using more and different tools and learning analytics knowledge to assist her to assess her own teaching:

> *When I have students' learning data, I would calculate mean and median scores to compare students' performance on different activities. Also, I would use variance to see about my teaching performance. If my teaching performance is good, then I should see the small variance in student scores. Regarding tools, I would just use Microsoft Excel to do all these data analysis, because I don't want to use tools that are too complicated to understand. (Week 1: before the first learning analytic tutorial)*
>
> *Based on the data, for students' learning outcomes, I can use data visualization to visualize students' learning outcomes to help me better understand their learning progress. Also, I am able to use correlation analysis and regression analysis between my teaching skills and students' learning results. With regard to tools, I will still use Excel as my default tool to use, but I am now*

> *also open to other data analysis tools that can help me perform the same data analysis functions. (Week 3: after the last learning analytic tutorial)*

Cindy. *Cindy* was a former full-time English teacher at a high school. She did not share her age, but she reported that she had 6 years of full-time teaching experience in the past. At the time this case study was conducted, she was pursuing her master's degree and has temporarily stopped teaching. She shared that she had previously used Schoology, an LMS platform, for less than a year for her teaching. The LMS functions she has used as a teacher included upload assignment, course reading, video, monitoring students' course participation, organizing course materials, and the like. The learning analytics functions she has used in teaching included checking students' learning progress and outcomes through data dashboards. Compared to other participants, *Cindy* had the most formal teaching experience and the most experience using LMS learning analytics in teaching. However, when she was asked the question *"How comfortable do you feel about helping your colleagues with their statistical questions?"* before the tutorials started, *Cindy*'s answer was 1, *"not comfortable,"* on a scale from 1 to 5, where 1 indicated *"not comfortable"* and 5 indicated *"very comfortable."* She was not confident about her statistical knowledge and skills before the professional development started.

With regard to her change in her learning analytics knowledge, *Cindy* showed improvement, where her score rose from 63 points in the pretest to 85.2 points in the posttest. When breaking down the questions by learning analytics topics, *Cindy* showed that she had a pretty solid understanding of mean and median in statistics—she received a full score for questions of those concepts in the pretest and posttest. She made a noticeable improvement in variance and correlation questions as her score changed from 63 points in the pretest to 74.1 points in the posttest. The area in which *Cindy* showed the largest improvement was regression. In the pretest, *Cindy* received zero points for the regression questions, but attained a high score of 90 points afterwards. It was unknown if the zero point from her pretest was due to her lack of regression knowledge or because she did not have enough time to answer the regression questions.

When examining *Cindy*'s PK, TPK, teaching efficacy, and teacher resiliency (see Figure 28), the results showed that, overall, there was improvement on these outcome measures for her. Between the first and second weeks of the professional development, her PK changed from 6.2 to 6.7 points on a 7-point Likert scale. Interestingly, in the third week, her PK score decreased a bit to 6.2 points, the same score as in the first week. Her TPK score exhibited a steady increase from 6 points in the first week to 6.8 points in the last week on a 7-point Likert scale. Relatively, *Cindy*'s PK and TPK scores were high, especially compared to the previous two preservice math teachers, whose end-of-professional development PK and TPK scores were only around 5 points. Another interesting result about *Cindy* was her change of teaching efficacy and teacher resiliency. Her teaching efficacy score went down from 5.6 points to 4.8 points from the first to the second week. Then, the same score climbed to 5.8 points in the last week. Teaching efficacy was measured by using a 9-point Likert scale. This result indicated that *Cindy*'s perception of her teaching efficacy changed from neutral to negative from the first week to the second week, and then her perception became neutral to positive again in the last week. *Cindy*'s teacher resiliency improved significantly after the professional development. Her teacher resiliency rose from 4 points in the first week to 6 points in the last week on a 7-point Likert scale. Overall, although there was some obvious increase in *Cindy*'s TPK and teacher resiliency, her PK score remained high throughout the 3 weeks. When paralleling her interview responses with her change in TPK, teaching efficacy, and teacher resiliency, some interesting results emerged.

Figure 28. Change in *Cindy*'s PK and TPK

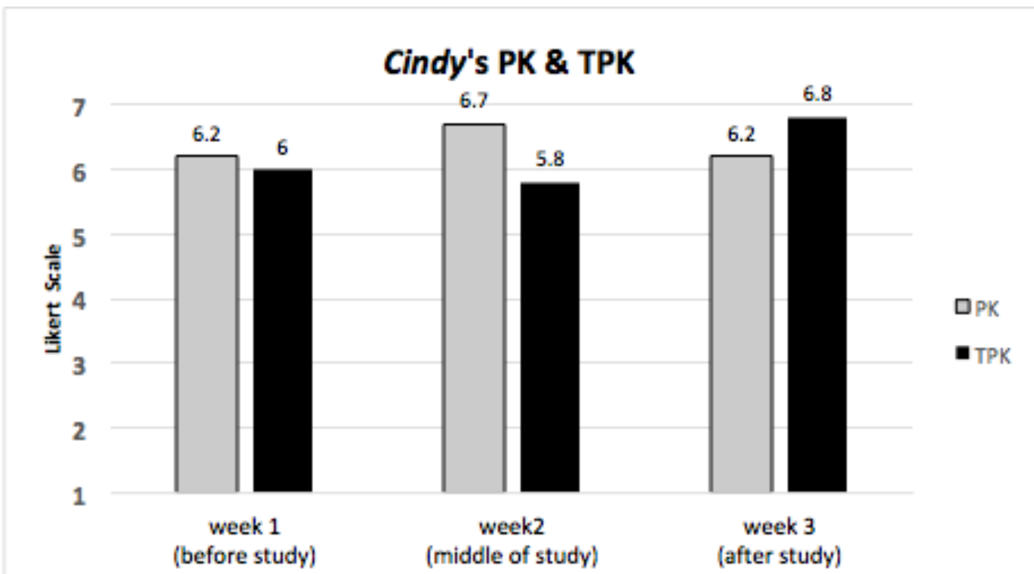


Figure 29. Change in *Cindy*'s teacher efficacy

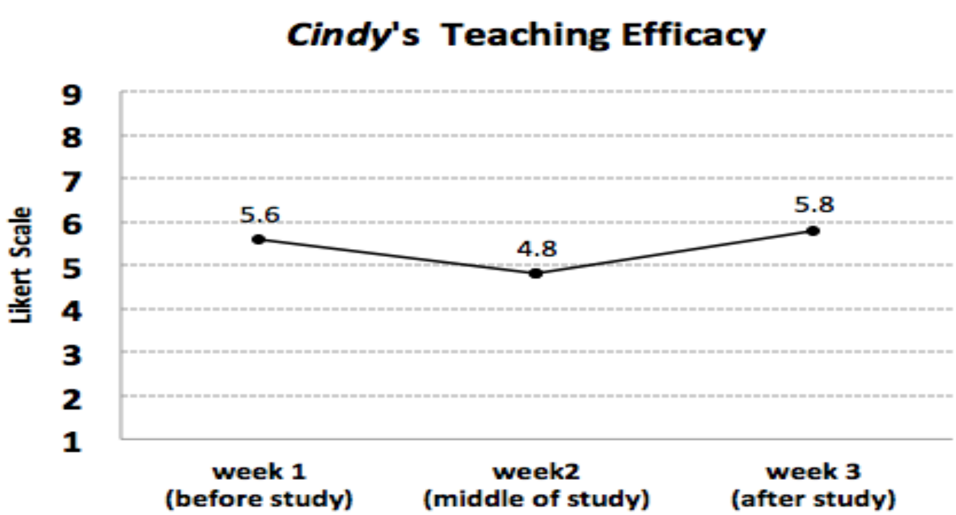
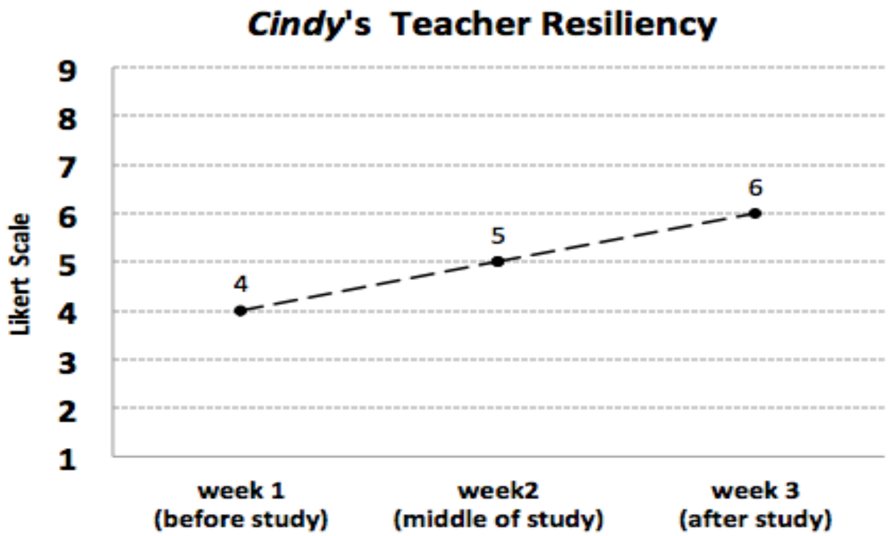


Figure 30. Change in *Cindy*'s teacher resiliency



When asked about the relevance and importance of weekly tutorial topics to her teaching, *Cindy*'s feedback suggested that she was much more familiar with the first week's topics, mean and median, than the topics in the second and third weeks, namely variance, correlation, and regression.

> *I used to only use mean value to see students' average performance. But now I know there is an alternative of using median. I also didn't know how to calculate median before and now I am able to. It is also to know that sometimes mean and median can tell a very different stories based on the same students' scores, so I can be careful about this.* (Week 1: mean and median)

From Cindy's responses, it could be inferred that the first week's tutorial content was more of a knowledge extension to learn about median based on her existing knowledge of mean. She also suggested her ideas about the pros and cons of using each approach to see students' performance. This might suggest that she has started to apply her learning analytics knowledge of mean and median at this time. However, her feedback about the second week's topics, variance and regression, showed less confidence in her knowledge acquisition and application of this topic:

> *This week I learned how to calculate variance, how to create a bar chart with error bar. Those are things I didn't know how to do before and it is helpful. Especially knowing the difference between variance and standard deviation. I was aware of these two concepts but didn't know the difference between them till this week's tutorial….* (Week 2: variance and correlation)

If her responses in the first and second weeks are compared, it is possible to see that she might not have been very familiar with the topics in the second week, as she said, *"I learned how to calculate…and I didn't know the difference [between variance and standard deviation] till this week's tutorial."* At the time of interview, *Cindy* might still be processing the new knowledge about variance and correlation and was not ready to apply this knowledge as she did with mean and median in the first week. The concepts of variance and correlation could have been challenging to *Cindy*. Her learning analytics scores showed that her pretest score was around 60 points and her posttest score was around 70 points on the variance and correlation questions, respectively. In contrast, her posttest score on mean and median questions was a full score of 100 points and her posttest score on regression questions was a high score of 90 points. Also, compared to other participants, *Cindy* was the only teacher whose posttest score on variance and correlation was around 70 points, while the others achieved at least 80 points or higher on the same questions. All in all, the decrease in *Cindy*'s teaching efficacy between the first and second weeks might be explained by the presumption that she encountered some unfamiliar learning analytics concepts in the second week. But in the end, *Cindy*'s teaching efficacy score peaked in the third week back to the level she was at in the first week. Despite the fluctuation in the teaching efficacy score, *Cindy*'s teacher resiliency score was on a rise throughout the professional development. Her perception of teaching resiliency changed from neutral to rather positive in the end, which might also suggest that the non-incremental increase in her teaching efficacy did not affect her growth in teacher resiliency.

Cindy also shared how she planned to apply the learning analytics knowledge she learned from the professional development to her future teaching. She was able to be specific about connecting various learning analytics concepts with assessing her students' performance and her teaching. With regards to using mean and median, she shared:

> *Now I know that mean tends to be influenced by outlier scores, such as few really high scores from a few students. In that case and in my own teaching, I will consider both mean and median as a way to represent students' performance.* (Week 1: mean and median)

For variance, correlation, and regression, *Cindy* also suggested the approach she planned to take to use these learning analytics concepts:

> *I will use both mean and standard deviation to examine students' scores when I teach multiple concepts to my students. In that case, I can have a more comprehensive view of students' scores and their performance.* (Week 2: variance and correlation)

> *For regression, I think I can estimate the contribution each assignment makes toward exam score by using the coefficients in the model, so I can know which assignment to focus on to plan my teaching make improvement on for students' learning.* (Week 3: regression)

Cindy has the most experience in teaching and using LMS learning analytics of all the participants. When she was invited to answer the scenario question, *"How you find out your teaching skills and students' learning outcomes?"* there was a big difference in terms of how she would use LMS learning analytics. The following is what she shared before and after the professional development:

> *I used to use Schoology, which is a software through which I could see my students posts about the courses I taught. I could see if my students understood the content I taught by seeing if my students really used the materials I gave them and the presentation they gave. But in that software, most of the functions I used were sharing course materials, making announcements, and have students post their assignments there.* (Week 1: before the first learning analytics tutorial)

> *After the tutorials in this professional development, I have learned how to use different approaches to evaluate students' learning outcomes. In the past, I only used means to see students' average performance, but now I know that variance is also important. Because if the variance is high then that means students' performance very differently and that may have to do with my teaching. Also, I also know how to use regression to see how different activities contribute a test score so I can help students to review. Also, it is important to use graphs to see the patterns in students' performance. Moving forward, I will also use other indications such as variance, standard deviation, et cetera, but not just mean to check students' learning outcomes.* (Week 3: after the last learning analytic tutorial)

Daisy. *Daisy* was a former full-time English teacher at a middle school. She was 27 years old and had 3 years of full-time teaching experience in the past. She was currently pursuing her master's degree and has stopped teaching at the moment. She shared that she has used Blackboard and another Chinese App called "Yi-Xiao-Tong (翼校通)" in teaching for more than 2 years. The LMS functions she has used as a teacher included making course announcements and sending messages to students' parents. She has also used learning analytics functions in these tools to check students' learning outcomes, monitor students' learning, and make pedagogical suggestions. Of all participants, *Daisy* was more aware that there was a variety of learning analytics functions in different LMS, although she has not used them extensively. When she was asked the question *"How comfortable do you feel about helping your colleagues with their statistical questions?"* before the tutorials started, *Daisy*'s answer was 5, *"no* *opinion,"* on a scale from 1 to 5, where 1 indicated *"not comfortable"* and 5 indicated *"very comfortable."*

With regard to her change in her learning analytics knowledge, *Daisy* showed a large improvement when her score rose from 51.9 points in the pretest to 89.8 points in the posttest. Breaking down the questions by the learning analytics topics showed that *Daisy* already had a good command of knowledge of mean and median since her pretest and posttest scores on this topic were both higher than 90 points. She improved around 46 points on correlation and variance questions (44.4 to 90.7 points) between pretest and posttest question. She also made a noticeable improvement on regression questions as her score changed from zero points in the pretest to 70 points in the posttest. Just like the previous teacher *Cindy, Daisy* may have received zero points for regression questions because she did not have enough time to complete all those questions in the pretest.

When examining *Daisy*'s PK, TPK, teaching efficacy, and teacher resiliency (see Figure 31), it was found that she exhibited a different pattern in the quantitative measures compared to the other participants. First, there was nearly no change in her PK score between the first and third weeks (6.7 to 6.8 points). She had a little improvement in the TPK (5.8 to 6.3 points). Both PK and TPK were measured by using a 7-point Likert scale, so her final PK and TPK scores were rather high and showed she had a very positive perception of herself on this front. Surprisingly, *Daisy*'s teaching efficacy score was 7.5 points in the first and second weeks (9-point Likert scale), but her teaching efficacy score in the third week dropped to 5.5 points at the end of the professional development. This might have shown that her perception of her own teaching efficacy changed from very positive to somewhat neutral (i.e., *no opinion*). *Daisy*'s teacher resiliency scores remained around 5.5 points throughout the 3 weeks, implying that she had a positive but not strongly positive perception in this measure. The special aspect about *Daisy* was that her teaching efficacy score dropped from the second to the third week, but she had a high PK and TPK score throughout the 3-week professional development. Her teaching resiliency also remained constantly positive. When investigating her interview feedback more closely, I could potentially presume what caused this drop in her teaching efficacy without affecting the other measures.

Figure 31. Change in Daisy's PK and TPK

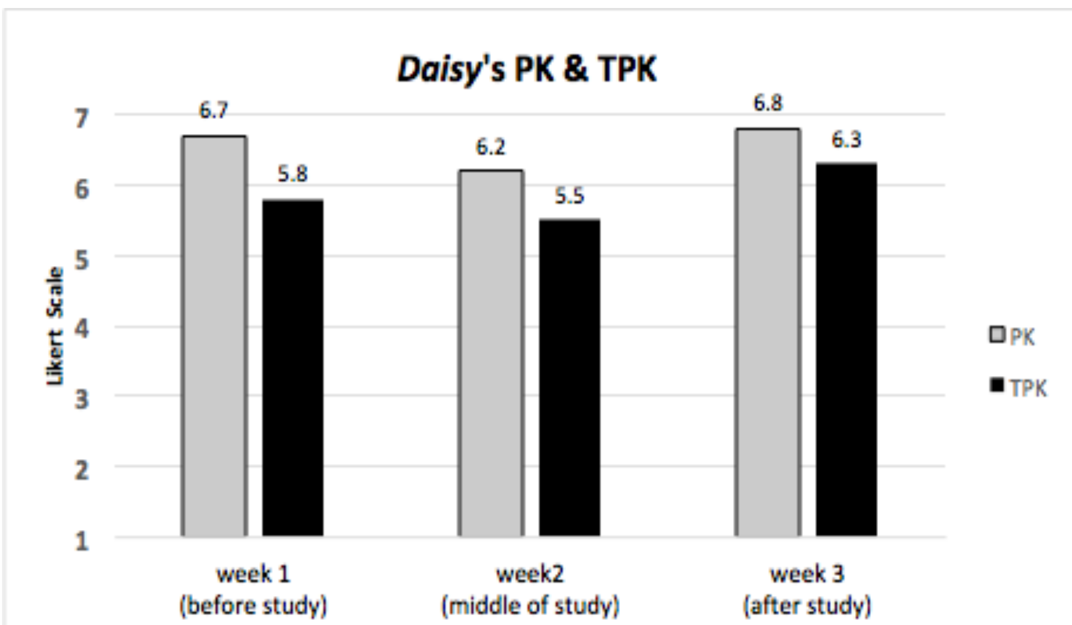


Figure 32. Change in *Daisy*'s teaching efficacy

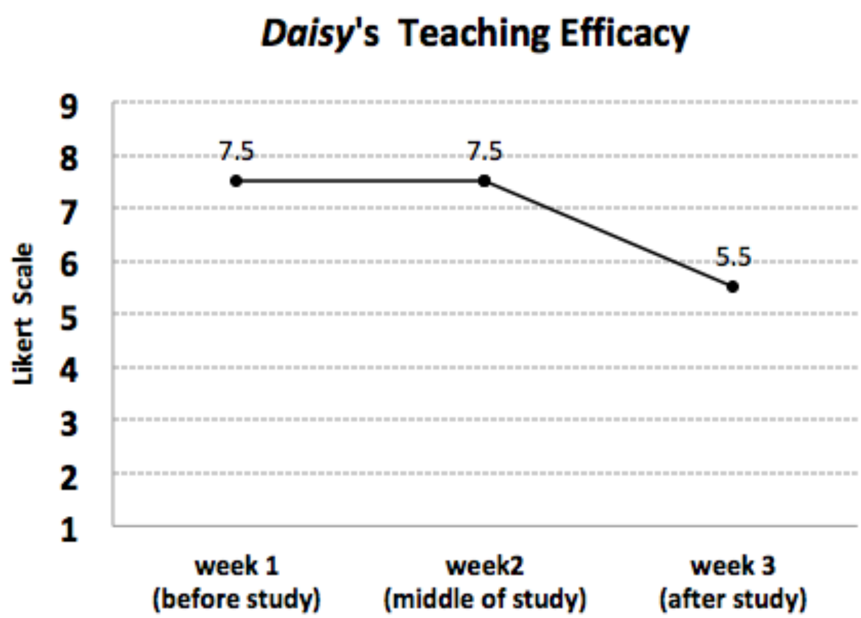
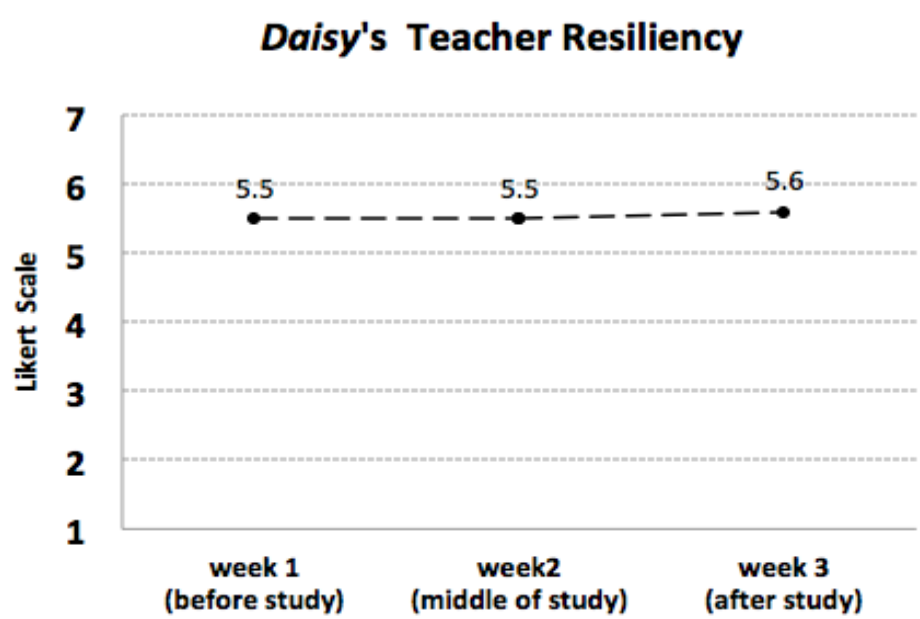


Figure 33. Change in *Daisy*'s teacher resiliency



From her responses during the interviews, *Daisy* tended to give different levels of detail when she described the relevance of different learning analytics concepts to her teaching. For example, for the topics of mean and median in the first week, and variance and correlation in the second week, she was able to elaborate the usefulness and importance of these knowledge in her teaching:

> *Although the concepts of mean and median were not new to me since I was using them when I was a teacher to evaluate students' performance, the technique to use Excel to calculate mean and median was useful. Also, using the bar chart to visualize the performance of the whole class, and also knowing when to use mean and median in teaching is important.* (Week 1: mean and median)

> *I think standard deviation is very useful especially when it comes with the mean as they can describe students' performance very well. Normally, teachers and parents put a lot of emphasis on mean, and they also tend to overlook the low-performing students but just look at the mean to estimate students' performance. So the standard deviation is really useful in this case. Also, the correlation chart is also helpful for teachers to tell the quality of and the relationship between different learning activities..*(Week 2: variance and correlation)

When looking at her feedback in the third week about her perception of regression, *Daisy* mentioned she was not familiar with the concept of regression although she acknowledged its importance:

> *I have never used a regression function to analyze students' exams or performance. I have also never seen my colleagues doing this before. I will use this kind of regression analysis in my teaching in the future. By checking regression coefficients, I will know which learning activity contributes the most the exam and I can plan my teaching accordingly.* (Week 3: regression)

Daisy's sharing about the regression in her teaching application sent a somewhat mixed message. On one hand, she sounded motivated to try implementing regression to adjust her teaching practices; on the other hand, she sounded as if she lacked confidence since she never used a regression analysis or has seen anyone using it in teaching until this professional development. This lack of confidence might also have resulted from her lack of solid prior knowledge of regression and its application. Regarding her scores of learning analytics knowledge questions, in the posttest *Daisy* was able to attain a full score of 100 points and a high score of 90 points on the questions based on mean, median, variance, and correlation statistical knowledge. In contrast, her posttest score on the regression question was 70 points. While 70 points was technically not a low score, it was apparently a departure from her performance on questions of other learning analytics topics. Concerning the decline in *Daisy*'s teaching efficacy score in the last week, this uncertainty about her ability to apply regression in her teaching may have been the cause. However, if any, this cause did not seem to have influenced *Daisy*'s PK, TPK, and teacher resiliency negatively.

In the end, like other participants, *Daisy* was also asked the scenario question after reviewing the teaching scenario and Megan's teaching scenario. Daisy's response to the question *"How do you find out your own teaching?"* prior to the tutorials centered on her past teaching experience and the technological tools she has used before. It showed that she was already using learning analytics to help her assess her own teaching and students' performance:

> *I would adjust my teaching based on my students' performance and learning outcomes. For example, I will look into their assignment and course quizzes or test scores. Also, I would have conversations with my students at different levels about their feelings about the course I teach. For tools, I used to use an App, in which if I type students' scores in it, it will predict the likely performance and learning obstacles a student is likely to achieve and encounter. Another App I used could help me know the patterns in the mistakes students are likely to make. It could help me adjust my teaching and help students to learning better.* (Week 1: before the first learning analytics tutorial)

After the 3-week learning analytics tutorials, *Daisy*'s answer became rather general when asked the same question:

> *I would say, after three weeks of tutorials, I can be more clear about my teaching performance on my different parts of teaching work. Also, I can know which learning activities I should put more energy on to help my students learn better.* (Week 3: after professional development)

Based on her response, it is possible that *Daisy* might have recalled her learning experience about correlation and regression when she answered this scenario question since knowing the contribution of different learning activities was the focus of the tutorials that taught correlation and regression. However, she did not elaborate with further details about her specific approaches as she did at the beginning of the professional development.

Ellen. *Ellen* used to be an elementary school where she taught English for half a year in the past. *Ellen* was 28 years old and has stopped teaching as a full-time teacher to pursue her master's degree. She has used Canvas, an LMS, as a student for a year. She said that she has never used any LMS or learning analytics in teaching in the past. She gave 3 points (*no opinion*) to the question *"How comfortable would you feel about answering your colleagues' statistical questions if they come to you for help?*"

Ellen showed tremendous improvement in her learning analytics knowledge. On average, her scores between the pretest and posttest improved the most among all participants. Her total improvement was around 50 points (38.9 to 88.9 points). Breaking down the questions by the learning analytics topics showed that *Ellen* already had a good command of knowledge of mean and median (pretest: 82.4 points; posttest: 100 points on accuracy score on mean and median). She was much less familiar with the topics of variance and correlation (pretest: 25.9 points; posttest: 88.9 points on accuracy score on variance and correlation) as well as the topic of regression (pretest: 0 points; posttest: 70 points on accuracy score on regression). In general, *Ellen* was able to achieve moderate to high levels of posttest scores for all different learning analytics questions.

Ellen's improvement in her learning analytics knowledge resonated with the patterns in her growth in PK, TPK, teaching efficacy, and teacher resiliency (see Figure 34). Her PK score improved from 4.3 to 5.7 points (7-point Likert scale). The change in her PK score implied that her attitude about her PK changed from *no opinion* to positive or confident. As for TPK, her score improved from 6 to 7 points (on a 7-point Likert scale). Her teaching efficacy also changed from 5.6 to 6.6 (on a 9-point Likert scale), implying that her perception of her teaching efficacy changed from *no opinion* to positive. In the end, her teacher resiliency score also grew from 5.5 to 6 points (7-point Likert scale).

Figure 34. Change in *Ellen*'s PK and TPK

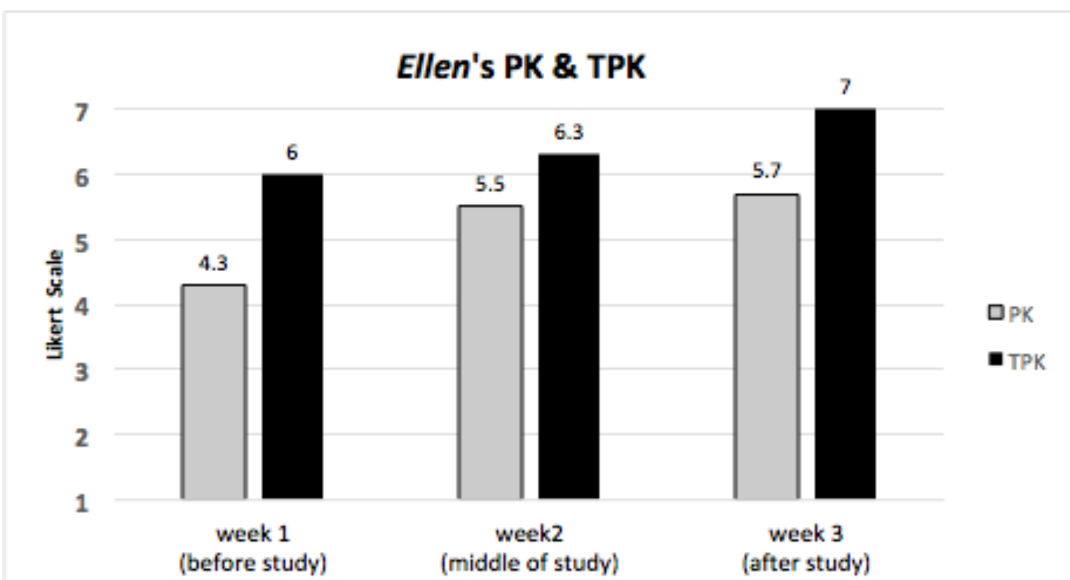


Figure 35. Change in *Ellen*'s teaching efficacy

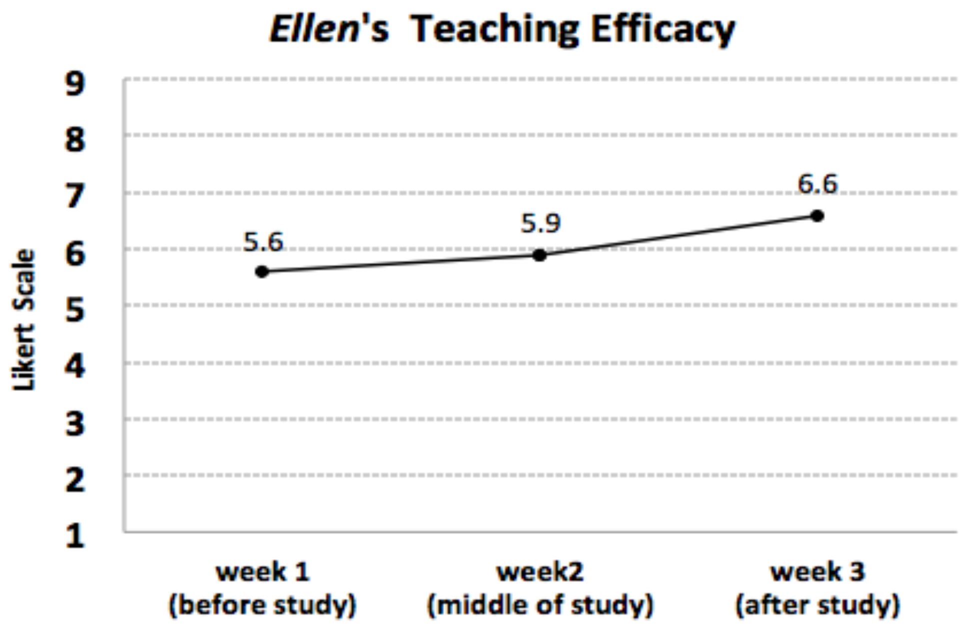
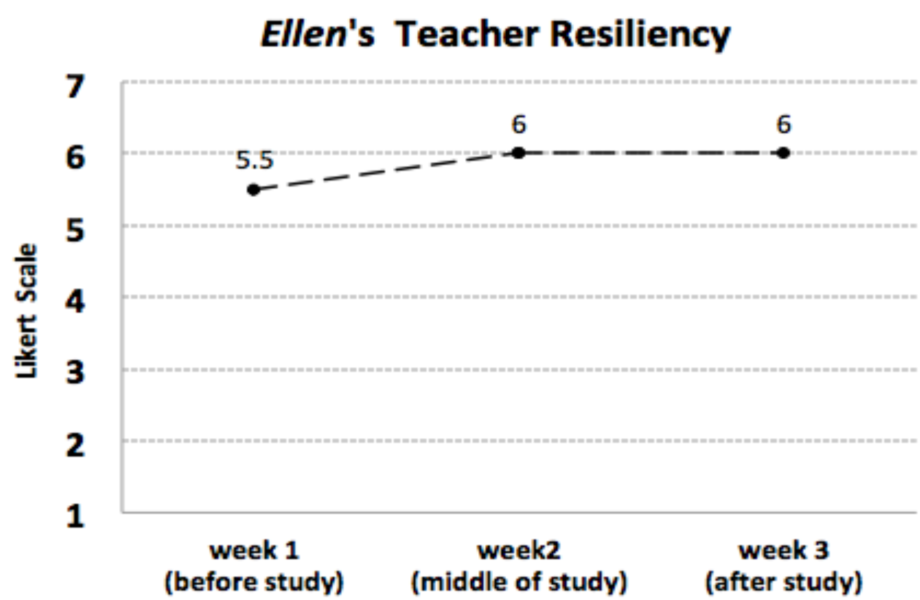


Figure 36. Change in *Ellen*'s teacher resiliency



Ellen's growth in the above outcome measures resonated with her interview feedback. Throughout different weeks of the learning analytics tutorials, she expressed that she felt the learning analytics topics introduced in the tutorials were useful and important for her teaching. For example, in the first week after she learned the concepts of mean and median through the tutorials, she shared:

> *I think oftentimes in my teaching I always use mean to generalize my students' performance. But after today's tutorial, I know that I need to be careful about individual differences between students and look at the whole picture instead of just looking at a single number such as mean value. Also, it is useful to know how to visualize the data in Excel and how to use different formulas to calculate the results I need to like mean and median.* (Week 1: mean and median)

Ellen's feedback suggested that she started to compare different methods to estimate students' learning performance (i.e., using mean or median). Her learning experience of using Excel to perform data visualization was also helpful for her. In the second week when variance and correlation were introduced in the tutorial, she gave similar positive feedback:

> *I think knowing the contrast between correlation and regression is very important. I think sometimes teachers tend to jump quickly into conclusion about our assumptions. So this is a good reminder that we need to be cautious of other possibilities when we are interpreting students' performance. Learning about correlation and knowing how to use data visualization certainly helps to analyze students' data. Last week we were learning about mean and median, and this week we are discussing variance and correlation. I could see how these learning analytics concepts add on top of each other.* (Week 2: variance and correlation)

After *Ellen* completed the tutorial and learned the topic of regression at the end of the third week, she again appreciated how the learning analytics topics were arranged to build on top of each other. She was also able to elaborate how she would use regression as a learning analytics approach to assess students' learning and her own teaching:

> *Regression is useful for me to take a look at my own teaching design and testing tools with regard to students' exam scores, so I can be sure all the learning activities are meaningful. Also, it is useful to learn about the meaning of p-value so I can be sure which activity is significant to put my emphasis on. The last point is that I am now able to use a more complicated approach to analyze my own teaching results. Till last week I could only do correlation, but now I am able to do regression so that I can further analyze students' learning and my teaching outcomes.* (Week 3: regression)

Furthermore, *Ellen* also explained specifically how she planned to use some of her learning analytics knowledge from the tutorials in her teaching. For example, for the topic of variance and correlation, she said:

> *I would use variance to give myself more ideas about students' performance. Especially I can know how students receive my teaching content differently. About correlation, I think it is a useful tool for teachers to test our assumptions about our teaching design especially based on the positive and negative correlations.* (Week 2: variance and correlation)

For knowledge of regression, *Ellen* also mentioned she could use it to assess students' learning and her own teaching as well:

> *I would use regression to analyze my students' performance in the future. I will also try to use it to predict students' performance and way[s] to improve my own teaching design.* (Week 3: regression)

Ellen's teacher resiliency seemed to grow parallel with her PK, TPK, and teaching efficacy. Although there was a lack of further statistical evidence to justify the causality, *Ellen*'s teacher resiliency showed an increasing pattern along with her PK, TPK, and teaching efficacy. She reached a high teacher resiliency score (6 out of 7) in the second and third weeks, the highest teacher resiliency score (as *Cindy*'s) among all participants.

At the beginning and end of the professional development, *Ellen* was asked to review the teaching scenario and answer the scenario question :*"You have read Megan's teaching scenario, now Megan wants to know how you find out your teaching skills and* *students' learning outcomes. How would you respond to her?" Ellen* said the following before the professional development:

> *I would understand my teaching skills based on the assessment of my students. For example, their scores and activities in my classroom. However, I didn't use any specific tools to make these assessments. I am a pretty rookie teacher so I don't know if there are tools that I can use. (Week 1: before the first learning analytics tutorial)*

After the 3-week learning analytics professional development, *Ellen* said the following as her answer to the same scenario question:

> *I would say my skills of evaluating students' learning outcomes have definitely improved a lot after three weeks of tutorials. Before the tutorials, I would use mean, median, and maybe variance. But now I am able to use regression analysis to see students' learning outcomes. This gives me more dimensions to see how my students are doing rather than just relying on the techniques I was using before. (Week 1: after the last learning analytics tutorial)*

In general, *Ellen*'s growth patterns for PK, TPK, teaching efficacy, and teacher resiliency were ideal in terms of the purpose and design of the learning analytics professional development in this dissertation research.

Power Analysis for a Relevant Future Study

The current case study with five novice teachers was exploratory, but the results demonstrated promising preliminary outcomes. The design of the current learning analytics professional development and its different measures can bear the potential to evolve into a full experimental study at a larger scale. Specifically, the same quantitative measures can be implemented before and after the learning analytics professional development to investigate its effects on participants' learning analytics knowledge, teaching efficacy, and teacher resiliency. After running a power analysis by using

G*Power 3.1 software to achieve a sufficient 0.8 statistical power and a satisfactory 95% confidence level with an estimated small effect size (i.e., 0.2), I would need approximately 199 participants for this experimental study. Participants' measures can be computed and analyzed by using two dependent matched samples t-test. In this scenario, I would make a statistical conclusion about the effects of the current learning analytics professional development. In the next chapter, I discuss the results of this case study along with the findings from the survey study. At the end of the chapter, I discuss the limitations and implications of this dissertation research, followed by a final summary.

Chapter V

GENERAL DISCUSSION

The findings from the case study provided several insights into the effects of case-based learning in professional development on learning analytics. This general discussion section reflects on the findings from both the learning analytics survey study and the case study.

Benefits of Applying Teaching Scenario in Learning Analytics Professional Development

In general, the professional development in learning analytics (i.e., intervention) had several positive effects on novice teachers. Except for one teacher (i.e., *Betty*), all other novice teachers who participated in the case study research significantly improved their learning analytics knowledge after 3 weeks of professional development in learning analytics. The only exception, *Betty*, did not exhibit an improvement mainly because she made some mistakes in reading the instructions of two questions in the posttest incorrectly, so she lost points which she could have been able to receive. Before the intervention, three of the novice teachers (i.e., the three English teachers) received rather low scores (around and below 60 points) in the learning analytics knowledge pretest. After the professional development, all five novice teachers were able to achieve over 80 points when they took the learning analytics knowledge posttest. This large increase in the regression score might have had to do with three of the five teachers running out of time and not being able to complete the pretest questions on regression. In general, all five novice teachers demonstrated the largest learning analytics knowledge growth in regression in statistics, compared to variance/correlation and mean/median knowledge. Furthermore, the five novice teachers' learning analytics knowledge growth spread evenly across three types of questions: basic, inference, and applied. This suggested that there is no serious knowledge gap in the question design itself, and the professional development could successfully extend novice teachers' learning analytics knowledge across basic-, inference-, and applied-level questions.

The 3-week learning analytics professional development also enhanced psychological outcomes for the five novice teachers. In general, all five novice teachers increased their PK and TPK after the intervention. For all the novice teachers, except *Ellen,* their PK seemed to be a more static characteristic that did not increase dramatically throughout the professional development. All five novice teachers showed a larger-degree of increase in their TPK compared to PK, most likely because of their intensive practice of using Excel to perform learning analytics in the learning analytics professional development.

In a general comparison, participants' increase in teacher resiliency was not as obvious as in their teaching efficacy during the intervention. The effects of the professional development on the novice teachers' teaching efficacy and teacher resiliency also seemed to be a mixed pattern. For novice teachers such as *Betty* and *Ellen*, their teaching efficacy and teacher resiliency increased in parallel throughout the 3 weeks. Their PK and TPK also grew in the same direction with teaching efficacy and teacher efficacy over time. On the other hand, for teachers *Abby* and *Cindy,* although their PK and TPK increased, there were some mismatched patterns between their teaching efficacy and teacher resiliency. When *Abby*'s and *Cindy*'s teaching efficacy declined, it did not seem to affect their teacher resiliency. This result may suggest that learning analytics professional development may influence teaching efficacy and teacher resiliency differently in some contexts. The interview data suggested that when *Abby*'s and *Cindy*'s teaching efficacy declined from the previous week, it was mostly likely because they had encountered some "reality check" for the learning analytics concepts with which they were less familiar, or perhaps they lacked relevant prior knowledge and needed more time to master those concepts. This result suggested two interesting insights. First, learning analytics professional development for novice teachers may need to take into account their prior knowledge of the professional development content before the professional development begins. It is possible that learning analytics professional development could reduce their teaching efficacy when there is a large knowledge gap for them or when they are not able to master the knowledge content in the allotted training time. Approaches such as using a pre-training prior-knowledge survey or a more personalized training curriculum would help on this front. The second interesting insight is that although many past studies have suggested the connection between teaching efficacy and teacher resiliency, and this research does not refute such a connection, teaching efficacy might be a characteristic which is more subject to immediate external events or influences, while teacher resiliency could be a more consistent psychological construct that is built on the teachers' long-term past teaching or life experience. Even so, after the professional development, all the novice teachers in the case study still exhibited slight growth in their teacher resiliency. One former English teacher, *Cindy*, also demonstrated a significant increase in her teacher resiliency (increased from 4-6 points on a scale of 7).

Influence of Teaching Experience on PK

The results of the case study suggested that teachers' backgrounds could moderate the influences of learning analytics professional development. Although generally all five novice teachers grew their PK after the professional development, when juxtaposing all five participants' PK scores and separating them by preservice and former teachers, the three former teachers had a higher average PK score than the in-service teachers by the end of the professional development. Also, at the beginning before any tutorials or learning activities, the former teachers, except for *Ellen*, had a higher PK score than the preservice teachers as well. This difference may reflect the effect of teaching experience. Another particularly interesting point of the result on PK is the moderation that the length of teaching experience seemed to have. To specify, the third former English teacher, *Ellen*, had only 6 months of formal teaching experience. The other two former English teachers, *Cindy* and *Daisy*, had 3 and 6 years, respectively, of formal teaching experience. By comparing their PK increase, it might be assumed that learning analytics professional development could have a larger impact on novice teachers' PK when they have little formal teaching experience but less of an impact on teachers who have several years of or no formal teaching experience. It is intuitive to assume that preservice teachers have a relatively lower average PK compared to former teachers, both before and after the professional development, due mostly to the lack of formal teaching experience. In contrast, while the degree of PK increase is similar for preservice and former teachers, the exception of *Ellen* may suggest that having some teaching experience (e.g., less than a year) may become a sweet spot for learning analytics professional development to increase PK. On the other hand, the change in PK may tend to be smaller when teachers have years of teaching experience through which their perception of their PK may have already been shaped.

Prior Experience of Using LMS Learning Analytics to Moderate Growth of TPK

Another important point is the experience of using LMS learning analytics and how it may moderate the effect of learning analytics professional development on teachers' TPK. The results showed that generally all participants increased their TPK after the professional development. But it is noteworthy that there was a larger TPK increase for the two preservice teachers (i.e., *Abby* and *Betty*) and the last former English teacher (i.e., *Ellen*). These three teachers increased their TPK by 2, 1, and 1 point(s), respectively. When examining these three teachers' information and teaching experience, they reported they did not have any experience with using LMS learning analytics functions in the past. In contrast, the other two participants, *Cindy* and *Daisy*, whose TPK increased a bit less than the previous three teachers, have used LMS such as Blackboard and Schoology for years in their past teaching. This result may suggest that while this learning analytics professional development could help teachers to increase TPK in general, this positive effect could especially be more significant for those who have not used any LMS learning analytics in teaching.

Confidence and Intention to Apply Learning Analytics to Teaching

There are several important findings from the learning analytics survey study. First, regarding the barriers teachers face in using LMS learning analytics in their teaching, the three major barriers are: (1) lack of awareness (e.g., teachers do not know if the LMS they are using has learning analytics functions); (2) lack of math/statistical skills; and (3) lack of computer skills to use learning analytics. In light of these barriers, it is clear that a successful learning analytics professional development must not only introduce what learning analytics is to teachers, but, more importantly, teachers will need to acquire the statistical and computer skills to perform learning analytics. Another critical finding from the survey study was the perception of usefulness of LMS learning analytics. In the survey study, the frequency of using LMS learning analytics was found to correlate positively with teaching efficacy and teacher resiliency. But this correlation existed only for teachers who had a prior perception that LMS learning analytics was useful for their teaching and curriculum design. In other words, prompting teachers to practice learning analytics exercises repeatedly would probably not benefit them much if they considered it as another routine or school policy without the belief that LMS learning analytics could actually help with their teaching.

All these findings from the survey study helped formulate the design of the learning analytics professional development in the case study. The purpose of the learning analytics professional development was threefold. First, the professional development was designed to help novice teachers develop statistical knowledge and computer skills to perform learning analytics. Through the pretest and posttests of the learning analytics knowledge questions, this research showed that novice teachers increased their learning analytics knowledge after the 3-week learning analytics professional development. Also, participants' interview feedback also suggested that they had become familiar with and capable of using Excel as a computer tool to conduct learning analytics.

Second, the objectives of the professional development was meant to establish novice teachers' confidence and capacity to use learning analytics to self-assess their teaching as well as their students' learning. Through participants' responses to the interview questions on the importance and relevance of different learning analytics topics, all five participants expressed that they considered learning analytics topics in this professional development important and useful in assessing their own teaching and students' learning outcomes. In the exploratory case study, although a stronger statistical test is required to make a more definitive conclusion, it is obvious that the five novice teachers had become more knowledgeable of utilizing learning analytics after the professional development. Some of the quantitative feedback from the five novice teachers also provided evidence to support this observation. For example, one of the novice teachers, *Abby*, shared how the learning analytics knowledge she gained after the professional development could help her monitor her teaching: *"As a teacher, sometimes I am not aware of the importance of each activity when I am designing them, so [using regression in learning analytics] is a good way to trace which assignment or quiz has the most impact on students' exams"* (after the third week's professional development). She also explained how the learning analytics knowledge of variance and correlation could help her assess students' learning processes: *"I will [use students' scores] to see the* *correlation between different student learning activities…and to find some clues about how different activities relate to each other and how they each relate to the exam in order to improve students' learning"* (after the second week's professional development).

Lastly, although a longitudinal study to trace participants' use of learning analytics was beyond the scope of this study, through the interview question *"How do you plan to apply the weekly learning analytics skills/knowledge in your teaching?"* and the scenario question "*Your teacher colleague, Megan, wants to know how would you find out your teaching performance and students' learning progress?"* it is possible to see from the five participants' responses that they developed the intention and initial plans to utilize learning analytics in their future teaching. For instance, some of them mentioned that *"they will use both mean and median to avoid the outlier student scores in order to get a correct estimate of students' performance as a group"* (*Cindy*). Other participants also mentioned that *"they would use variance to examine their own teaching performance to see if students receive their teaching practices equally or if there is a knowledge gap between students"* (*Betty, Daisy, Ellen*). The other participants also shared that *"I would use correlation and regression to help them determine which learning activities are crucial in preparing students for their exams"* (*Abby, Betty, Cindy*). These qualitative feedback statements could be the evidence to demonstrate participants' intention to integrate learning analytics into their future teaching. In sum, the results of the case study demonstrated that the learning analytics professional development could be an effective intervention not only to enhance novice teachers' knowledge and skills of learning analytics, but also to establish their perception that learning analytics could be useful in teaching and motivate them to develop various ideas to use it in their own teaching.

Limitations and Future Research

There were some limitations in this dissertation research. First, the size and the source of data collection for the survey study and the case study were limited. In the survey study, the number of preservice teachers was nine, while the number of in-service teachers was 47. The imbalanced number of preservice and in-service teachers inevitably reduced the representativeness of the results with regards to what kinds of LMS or learning analytics functions each group used, the similar and different barriers they encountered, and the comparison of two groups of teachers' TPK and teaching efficacy, among other aspects. Also, when participants were recruited for the survey study, they did not need to identify their schools. Therefore, there might be a risk of homogeneity in the survey results regarding the LMS or learning analytics functions participants used if many of them were from the same school. Future studies could consider using a larger teacher population to include teachers from different areas, school types, teaching experience, and other demographics to make the research results more representative. For the exploratory case study, it is worth mentioning that the recruitment process was disrupted by the COVID-19 pandemic. Several potential participants who were initially interested in joining this 3-week-long study dropped out of the study because they decided to relocate outside of New York City for their health and safety considerations. Unfortunately, this Act of God limited the number of participants. Yet, a small participant group provided the author with availability for an in-depth elaboration on the influence of the professional development on each participant. Due to the small sample size, the quantitative measures were analyzed mostly through descriptive statistics in this study. Future research could consider adopting a similar research structure with a larger sample size, which would offer opportunities to analyze the same quantitative measures through inferential statistics and an experimental design. In that case, interesting questions to be explored could include the correlation between TPK, teaching efficacy, and teacher resiliency, as well as examining salient predictors for teacher resiliency through regression analysis.

The second limitation was the authenticity of participants' feedback during the interviews in the professional development. All five participants were giving rather positive feedback with regards to the learning analytics skills and knowledge they acquired. They also expressed that these learning analytics concepts were highly valuable and useful for them, and they planned to integrate learning analytics into their teaching. However, since the researcher also played the facilitator role and all participants were aware that he was the designer of the professional development, they may have felt some pressure not to give positive feedback when asked various interview questions. Also, participants could have also been subject to the effect of social desirability to give the facilitator (i.e., author of this research) the interview feedback they thought best fit the facilitator's interests. A way to reduce pressure on participants to give positive feedback for future studies is to inform them that the facilitator has no interest conflicts in the outcomes of the professional development.

The last limitation was the timing of implementing posttest measures in the case study. Although during the tutorials the facilitator adopted a flexible schedule and professional development curriculum whereby participants would pace their learning, and although the facilitator also set different checkpoints to ensure participants' knowledge/ skills acquisition, all the posttest measures, including quantitative survey and interview questions, were implemented right after weekly tutorials. It is possible that the effects of the learning analytics professional development on some outcome measures in the case study (e.g., teaching efficacy, teacher resiliency) may appear more significantly with some latency. However, due to the design of the case study, participants were not given much leeway to reflect on and digest their learning experience of the weekly tutorials before they had to complete posttest questions. Future research may consider a longitudinal format for this type of research to see if the effects of learning analytics professional development could be measured at various time points after the professional development, and how would the effects differ in terms of their direction, magnitude, and continuity.

Implications

This dissertation research can contribute to the literature in three different ways. First, although past studies have shown that teachers' application of learning analytics and professional development which used actual teaching scenario can both enhance teaching efficacy (Dawson, McWilliam, & Tan, 2008; Zottmann et al., 2012), very little research has attempted to connect these two areas. The learning analytics professional development in this research utilized a teaching scenario in the learning analytics professional development for novice teachers. The positive results of the five novice teachers' learning outcomes provided valuable empirical evidence and pedagogical implications for how to operationalize professional development effectively in order to enhance teachers' PK, TPK, teaching efficacy, teacher resiliency, and learning analytics knowledge.

The second implication of this dissertation research is the benefits which learning analytic professional development may be able bring into many teacher educations programs. Many schools are motivated to incorporate a variety of learning management systems (LMS) in their classroom to improve students' learning by analyzing the student data they collect. However, in most teacher education programs across the country, preservice teachers are not trained to utilize students' data and improve their teaching practices based on data analyses. As the exploratory case study in this dissertation research showed, though some preservice teachers might have had a healthy mathematical or statistical foundation to understand the information they viewed through learning analytics, there remains a large gap between understanding analytical results and putting the analytical findings into pedagogical actions for the novice teachers without proper learning analytics professional development. There are two potential approaches to address this gap. For preservice teachers, learning analytics could be integrated into the curriculum in the teacher education programs. In this case, preservice teachers will have opportunities to train and cultivate their technical and statistical knowledge relevant to learning analytics before they begin teaching formally. For in-service or experienced teachers, given that it might be challenging for them to complete a semester-long learning analytics coursework with their work schedules, a short-term learning analytics summer institute or professional development during the weekends could be a feasible solution.

Another implication of this study is to extend the definition of teachers' analytical competence. Although past studies have suggested that professional development which used teaching scenarios such as teaching videos could effectively increase teachers' analytical competence (Zottmann et al., 2012), analytical competence in this area has a generic definition, described as teachers' ability to observe, analyze, and assess classroom situations that can help them improve teaching (Goeze et al., 2014). This research has concretized the conventional definition of teachers' analytical competence by extending it to teachers' ability, confidence, and planned strategies to utilize learning analytics in assessing their own teaching and students' learning outcomes in an actual teaching scenario. Also, by connecting teachers' enhanced learning analytics skills to teaching efficacy and teacher resiliency, this research has provided an important reference to address the current issue that novice teachers lack skills to assess and improve their teaching as well as their consequential professional fatigue, frustration, and burnout.

In the end, the findings in this research also offer valuable economic and policy implications. While other contextual factors may still be likely to lead to high turnover rates for novice teachers in the United States, such as school poverty, lack of school leadership support, and so on, this research focused on one of the major challenges in most U.S. teacher education programs, in which novice teachers need a more effective approach to improve their pedagogical practices with the assistance of learning analytics. Similar learning analytics professional development with a special focus on novice teachers could be conducted at a larger scale and could potentially alleviate teacher turnover and derivative economic costs in the United States. In the long run, students could also benefit from teachers who are empowered to teach more effectively and efficaciously to improve their learning performance.

Summary

This dissertation research aimed to tackle the issue of high turnover rate for novice teachers because of their lack of teaching efficacy and teacher resiliency. This research proposed learning analytics professional development as an effective intervention to help novice teachers teach more effectively and efficaciously by better assessing their teaching practices. The results of this research showed that learning analytic professional development is an effective approach to improve novice teachers' learning analytics knowledge, teaching efficacy, and teacher resiliency, and to develop higher confidence and intention to use learning analytics in future teaching.

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Appendix A

Questionnaire

TEACHERS COLLEGE

COLUMBIA UNIVERSITY

PROGRAM IN COMMUNICATION, MEDIA, AND LEARNING TECHNOLOGIES DESIGN (CMLTD)

Learning Management System (LMS) Learning Analytics in Teaching Research Questionnaire

You are invited to participate in our research on "**using Learning Management System (LMS) learning analytics in teaching**". It is believed that LMS learning analytics bear potentials for improving teaching and curriculum design. This research is being done to investigate how current educators are utilizing LMS learning analytics in association with their teaching in the classroom. Your feedback for this current questionnaire will help us understand how to help educators better use LMS for their teaching in the classroom. Your feedback will be kept anonymous and confidential. This questionnaire will take about **5 minutes** to complete. If you have any questions, please let us know so we can further explain before you start. If you agree to participate, please verbally indicate the following: "*I understand and consent to participate*".

(1) Gender:

☐ Male
☐ Female
☐ Preferred way to identify: __________

(2) Age: ______

(3) What is your field of study? (e.g. majors, degrees, certificates):

____

(4) Which subject(s) do you teach?

____

(5) Which school do you teach at? (optional)

____

(6) Which grade level do you teach?

☐ Elementary school
☐ Middle school
☐ High school
☐ Other: ____________

(7) Which kind of school do you teach at?

☐ Public school
☐ Private school
☐ Charter school
☐ Magnet school
☐ College preparatory school
☐ Other: ___________

(8) Which learning management system (LMS) do you use for teaching? (select all that apply)

☐ Google Classroom
☐ Moodle
☐ Canvas
☐ Blackboard
☐ Class Dojo
☐ Schoology
☐ Edmodo
☐ Quizlet
☐ Haiku Learning
☐ Pearson SuccessNet
☐ Desire2Learn
☐ Other: _____________

(9) At your school, how is LMS introduced to the teachers/staff? (select all that apply)

☐ Seminar/workshop ☐Tutorials ☐Webinar

☐ Other: ______________________________

(10) Which kinds of general LMS functions are you using? (select all that apply)

☐ Upload assignments, readings, videos, etc.
☐ Track students' attendance
☐ Make course announcement
☐ Group students for course activities
☐ Grading/Assessment
☐ Interact with students (e.g. discussion board, message)
☐ Generate learning content
☐ Create tests
☐ Other: ______________________________

(11) What kinds of LMS data analytics functions are you using? (select all that apply)

☐ None
☐ Monitor students' course participation
☐ Check individual student's learning progress
☐ Examine average class learning performance
☐ Predict students' learning outcomes
☐ Send periodical learning report to yourself (teacher)
☐ Send notification to students based on certain student actions
☐ Visualize students' activities in dashboard
☐ Other: _

(12) What are the major reason(s) that you may not use LMS data analytics functions? (select all that apply)

☐ I don't know if the LMS I am using has data analytics functions
☐ Objection from students (e.g. students don't know how to use, have no Internet access)
☐ Objection from parents (e.g. privacy concern)
☐ Not so familiar with computer skills
☐ Not so familiar with math/statistical knowledge
☐ LMS data may be used against me on my work performance evaluation
☐ LMS data can't truly reflect students' learning outcomes
☐ Other: ____

(13) Which aspect(s) of student learning do you think LMS data can reflect? (select all that apply)

☐ Learning outcome
☐ Learning process
☐ Opportunities to enhance students' knowledge/skills
☐ Identification of low-performing/ at-risk students
☐ Timing to implement learning intervention
☐ Other: ________________________

(14) LMS data analytics provide useful information to improve my teaching.

☐	☐	☐	☐	☐
1 Strongly Disagree	2	3 No Opinion	4	5 Strongly Agree

(15) LMS data analytics make curriculum/instructional design more effective.

☐	☐	☐	☐	☐
1 Strongly Disagree	2	3 No Opinion	4	5 Strongly Agree

(16) Do you feel you can choose technologies that enhance your teaching approaches for a lesson?

☐	☐	☐	☐	☐
1 Strongly Disagree	2	3 No Opinion	4	5 Strongly Agree

(17) Do you feel you can choose technologies to enhance students' learning for a lesson?
(18)

☐	☐	☐	☐	☐
1 Strongly Disagree	2	3 No Opinion	4	5 Strongly Agree

(19) Do you feel you can think critically about how to use technology in your future classroom?

☐	☐	☐	☐	☐
1 Strongly Disagree	2	3 No Opinion	4	5 Strongly Agree

(20) Do you feel you can adapt different technologies to different teaching activities?

☐	☐	☐	☐	☐
1	2	3	4	5
Strongly Disagree		No Opinion		Strongly Agree

(21) To what extent can you use a variety of assessment strategies?

☐	☐	☐	☐	☐	☐	☐	☐	☐
1	2	3	4	5	6	7	8	9
Nothing		Very Little		Some		Quite A Bit		A Great Deal

(22) To what extent can you provide an alternative explanation or example when students are confused?

☐	☐	☐	☐	☐	☐	☐	☐	☐
1	2	3	4	5	6	7	8	9
Nothing		Very Little		Some		Quite A Bit		A Great Deal

(23) To what extent can you craft good questions for your students?

☐	☐	☐	☐	☐	☐	☐	☐	☐
1	2	3	4	5	6	7	8	9
Nothing		Very Little		Some		Quite A Bit		A Great Deal

(24) How well can you implement alternative strategies in your classroom?

☐	☐	☐	☐	☐	☐	☐	☐	☐
1	2	3	4	5	6	7	8	9
Nothing		Very Little		Some		Quite A Bit		A Great Deal

(25) How well can you respond to difficult questions from your students?

☐	☐	☐	☐	☐	☐	☐	☐	☐
1	2	3	4	5	6	7	8	9
Nothing		Very Little		Some		Quite A Bit		A Great Deal

(26) How much can you do to adjust your lessons to the proper level for individual students?

☐	☐	☐	☐	☐	☐	☐	☐	☐
1	2	3	4	5	6	7	8	9
Nothing		Very Little		Some		Quite A Bit		A Great Deal

(27) To what extent can you gauge student comprehension of what you have taught?

☐	☐	☐	☐	☐	☐	☐	☐	☐
1	2	3	4	5	6	7	8	9
Nothing		Very Little		Some		Quite A Bit		A Great Deal

(28) How well can you provide appropriate challenges for very capable students?

☐	☐	☐	☐	☐	☐	☐	☐	☐
1	2	3	4	5	6	7	8	9
Nothing		Very Little		Some		Quite A Bit		A Great Deal

(29) How do you feel about your workload at school?

☐	☐	☐	☐	☐	☐	☐	☐	☐
1	2	3	4	5	6	7	8	9
Nothing		Very Little		Some		Quite A Bit		A Great Deal

(30) I feel that my school provides support in professional development for improving teaching.

☐	☐	☐	☐	☐
1	2	3	4	5
Strongly Disagree		No Opinion		Strongly Agree

(31) I feel that my school leadership is supportive of implementing new technologies for improving teaching

☐	☐	☐	☐	☐
1	2	3	4	5
Strongly Disagree		No Opinion		Strongly Agree

(32) Have you thought about quitting being a teacher? If so, when (e.g. 1st year, 2nd year of teaching) and why?

- End of questionnaire -

Appendix B

Demographic and Basic Information Survey

(1) Your name (for data analysis purpose only):

(2) Gender: _

- ☐ Male
- ☐ Female
- ☐ Preferred way to identify: __

(3) Age: ______

(4) Have you ever taken a teaching position before?

- ☐ Yes
- ☐ No

If your response is "Yes", please indicate:

(4.1) How long is your teaching experience: _________________

(4.2) Where have you taught? (e.g. learning center, after school program, tutoring): ____

(5) Which year are you in for your teacher education program (if applied)?

____

(6) Which subject do you plan to teach in the future/have you taught?

____

(7) Which grade level do you plan to teach in the future/have you taught?

- ☐ Elementary school
- ☐ Middle school
- ☐ High school
- ☐ Other: ____________________________________

(Please continue on the next page)

Experience of Using Learning Management System (LMS)

(8) Which learning management system (LMS) have you used as a "student" ? (select all that apply)

- Google Classroom
- Moodle
- Canvas
- Blackboard
- Class Dojo
- Schoology
- Other: _

(9) Which learning management system (LMS) have you used as a "teacher" ? (select all that apply)

- Google Classroom
- Moodle
- Canvas
- Blackboard
- Class Dojo
- Schoology
- Other: _

(10) How many years have you used LMS in teaching?

- I have never used a LMS to teach
- Less than 1 year
- Between 1 and 2 years
- More than 2 years
- Other: _

(11) Which kind(s) of general LMS functions have you used? (select all that apply)

- Upload assignments, readings, videos, etc.
- Monitor students' course participation (e.g. attendance, discussion forum)
- Make course announcement & reminders
- Group students for course activities
- Grade students' assignments, quizzes, tests, etc
- Interact with students (e.g. discussion board, message)
- Organize course & lesson materials
- Administer tests & quizzes
- Other: _

(12) Which kind(s) of general LMS functions have you used? (select all that apply)

- ☐ None
- ☐ Check class & individual student's learning progress
- ☐ Check class & individual student's learning outcomes
- ☐ Identify & alert low-performing/ at-risk students
- ☐ Predict students' learning outcomes
- ☐ Monitor students' learning to make pedagogical suggestions for teachers
- ☐ Identify appropriate pedagogical approach & detect the timing to intervene
- ☐ Other: ____

(13) If a colleague has some statistical questions that (s)he wants to ask you for your help, how comfortable do you feel about helping him/her?

Not comfortable	1	2	3	4	5	Very comfortable

(end of this survey—Thank you!)

Appendix C

Week 1: Pretest Survey

Your name (for data analysis purpose only): ____________________

Data Analytics Knowledge Questions

1.1 To get a sense of students' average performance, you can calculate mean. Given two student groups' scores below, please write down your calculation process and the mean for each group below:

Group 1 scores: (60, 77, 55, 97, 81)
Group 2 scores: (88, 42, 30, 95, 100)

Please put your calculation process here:

Group 1 mean: _____________
Group 2 mean: _____________

1.2 To get a sense of students' average performance, you can also calculate median. Given the same student scores as in the previous question, please write down the median for each group below:

Group 1 scores: (60, 77, 55, 97, 81)
Group 2 scores: (88, 42, 30, 95, 100)

Please put your calculation process here:

Group 1 median: _____________
Group 2 median: _____________

1.3 If there is a new score 60 to be added into each of the two group scores, what is the new mean for each group?

Group 1 scores: (60, 77, 55, 97, 81)
Group 2 scores: (88, 42, 30, 95, 100)

Please put your calculation process here:

Group 1 mean: _____________
Group 2 mean: _____________

1.4 If there is a new score 60 to be added into each of the two group scores, what is the new median for each group?

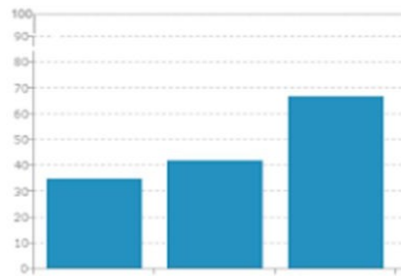
Group 1 scores: (60, 77, 55, 97, 81)
Group 2 scores: (88, 42, 30, 95, 100)

Please put your calculation process here:

Group 1 median: _____________
Group 2 median: _____________

1.5 Which of the following data graph can accurately represent the average performance of the whole class on 3 different class assignments? (select one answer but provide reasons for all the options)

◯ Bar chart



Why do you choose/not choose bar chart: ________________

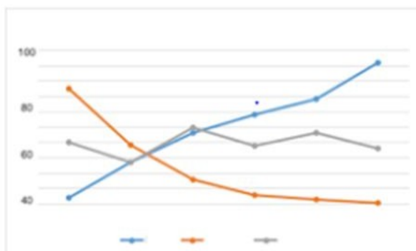
____

____

____

____

◯ Line chart



Why do you choose/not choose line chart: ________________

____

____

____

____

1.6 Suppose you have six student scores on a math quiz as shown below, will you choose mean or median to better represent the center of these student scores? (select one answer)

Students' math quiz scores: (79, 94, 81, 10, 96, 97)

◯ 1. Mean
◯ 2. Median
◯ 3. I am not sure

Please explain your answer:

2.1 Variance can be generally defined as the average distance of students' scores from their group mean. Given two groups of students' scores below, please write down your calculation process and the variance for group 1 & 2 separately:

Group 1 scores: (42, 65, 58, 85)
Group 2 scores: (66, 81, 74, 69)

Please put your calculation process here:

Group 1 variance: _____________
Group 2 variance: _____________

2.2 For the same two sets of student scores in the previous question, if there is a new score 100 to be added into each group, which of the following is true? (select all that apply)

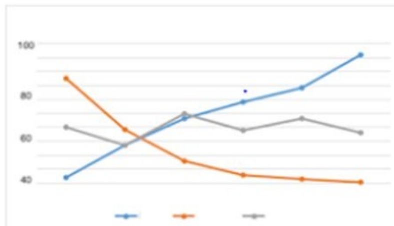
- ☐ 1. The variance will not change in both group 1 & group 2
- ☐ 2. The variance will increase in both group 1 & group 2
- ☐ 3. The variance will decrease in both group 1 & group 2
- ☐ 4. The variance will increase more in group 1 than in group 2
- ☐ 5. The variance will increase more in group 2 than in group 1
- ☐ 6. I am not sure

2.3 If you have two new student groups, and the variance for group 1 is 78 while the variance for group 2 is 18, how will you interpret students' performance in group 1 and 2 regarding their variance? (select one answer)

- ◯ 1. Students' performance in group 1 is more similar to each other than that in group 2
- ◯ 2. Students' performance in group 1 is less similar to each other than that in group 2
- ◯ 3. In order to know the variation of student performance in both group, you can’t use variance
- ◯ 4. I am not sure

2.4 Which of the following data graph can accurately represent the variance within each of the three student test scores? (select one answer but provide reasons for all options)

◯Line chart



Why do you choose/not choose line chart: ________________

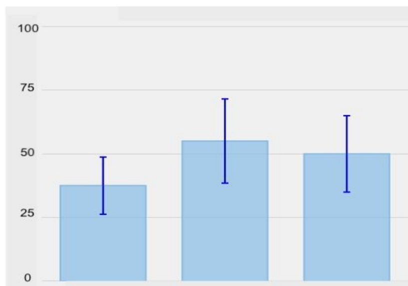
____

____

____

____

◯Bar chart



Why do you choose/not choose bar chart: ________________

____

____

____

____

2.5 Suppose you have the mean and variance of students' class performance below, what can you tell from the mean and variance?

	1st quiz	**2nd quiz**	**3rd quiz**
Class A	mean: 85 variance: 318	mean: 90 variance: 88	mean: 80 variance: 35
Class B	mean: 70 variance: 50	mean: 80 variance: 190	mean: 90 variance: 318

Please explain your answer:

3.1 A correlation coefficient (Pearson's r) is a numerical measure of a statistical relationship between two variables ranging from −1 to +1. If you have identified that r = 0.8 between students' quiz 1 & 2 score, and r = 0.2 between quiz 1 & 3, and r= -0.3 between quiz 2 & 3, which of the following is true? (select all that apply)

** assuming all correlation coefficients are statistically significant*

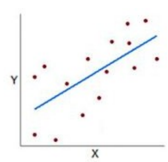
☐ 1. There is a strong positive relation between quiz 1 & 2 score
☐ 2. There is a strong negative negative relation between quiz 2 & 3 score
☐ 3. There is a weak positive relation between quiz 1 & 3 score
☐ 4. There is a moderate positive relation between quiz 1, 2, & 3
☐ 5. I am not sure

Please explain your answer:

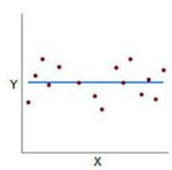
3.2 Please pair each of the following correlation coefficients (Pearson's r) with their corresponding data visualization which best describes the relationship between X and Y

r = 0 : _______ **r = +1 :** _______ **r = - 1:** ______ **r = + 0.7:** ______ **r = - 0.7:** ______

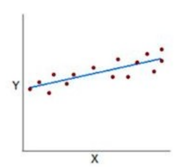
A.



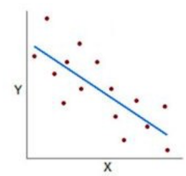
B.



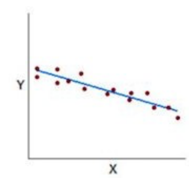
C.



D.



E.



3.3 Given correlation coefficients between scores of 5 different learning activities below, how will you interpret this result? (select all that apply)

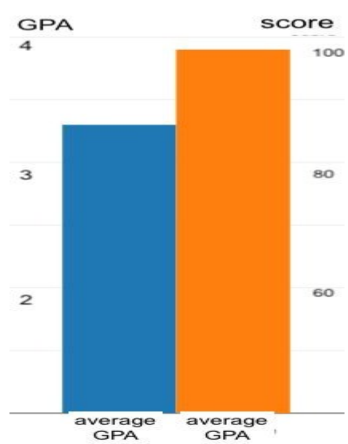
	Quiz 1	Quiz 2	Assignment 1	Assignment 2	Practice Exam	Final Exam
Quiz 1	1.0	0.1	0.7	0.2	0.3	?
Quiz 2	0.1	1.0	0.1	0.8	0.85	?
Assignment 1	0.7	0.1	1.0	0.01	0.04	?
Assignment 2	0.2	0.8	0.01	1.0	0.9	?
Practice Exam	0.3	0.85	0.4	0.9	1.0	?

- ☐ 1. Students who do well on quiz 1 are likely to do well on quiz 2
- ☐ 2. Student who do well on assignment 1 are likely to do well on assignment 2
- ☐ 3. Students who do well on assignment 2 are likely to get high score on the exam
- ☐ 4. Students who do well on quiz 1 are likely to do assignment 1 well
- ☐ 5. None of above

Please explain your answer:

3.4 Which of the following graph can inform how students' exam scores correlate with their GPA? (select one answer but provide reasons for all the options)

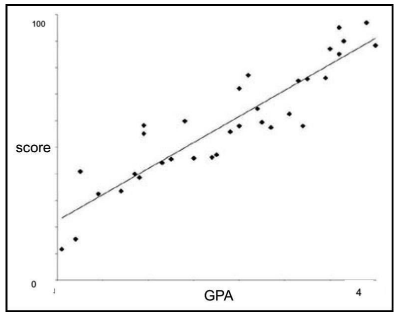
○ Parallel bar chart



Why do you choose/not choose parallel bar chart:

____
____
____
____
____

◯ Scatterplot



Why do you choose/not choose scatterplot: ________________

____
____
____
____

3.5 Given the same correlation table as in the previous question, what will be some appropriate pedagogical suggestion(s) to make based on the correlation coefficients ? (select all that apply)? (select all that apply)

	Quiz 1	Quiz 2	Assignment 1	Assignment 2	Practice Exam	Final Exam
Quiz 1	1.0	0.1	0.7	0.2	0.3	?
Quiz 2	0.1	1.0	0.1	0.8	0.85	?
Assignment 1	0.7	0.1	1.0	0.01	0.04	?
Assignment 2	0.2	0.8	0.01	1.0	0.9	?
Practice Exam	0.3	0.85	0.4	0.9	1.0	?

☐ 1. The practice exam involves most content knowledge from Quiz 1 and Assignment 1
☐ 2. The practice exam involves most content knowledge from Quiz 2 and Assignment 2
☐ 3. The practice exam involves most content knowledge from Quiz 1 and Quiz 2
☐ 4. The practice exam involves most content knowledge from Assignment 1 and Assignment 2

3.6 Following the previous question, the final exam will involve 30% of the content from the two quizzes, and 70% of the content from the two assignments. If you will help students review those learning activities, which learning activities would you focus on as the best approach in order to help the students prepare for the final exam? (select one answer for each of the sub-questions below)

(1) ◯ Assignment 1 & quiz 1 **Or** ◯ Assignment 2 & quiz 2

(2) ◯ Quiz 1 & Quiz 2 **Or** Assignment 1 & Assignment 2

4.1 Which of the following is the purpose of using regression analysis? (select all that apply)

- ☐ 1. Understand the causal relationship between a dependent variable and independent variable(s)
- ☐ 2. Forecasting (predicting) an outcome based on effect of independent variable(s)
- ☐ 3. Identify the trends of dependent variable given the change in the independent variable(s)
- ☐ 4. Identify if the difference between two sets of values is statistically significant

4.2 Please link each of the following questions with the type function in regression analysis in the following:

1. Does the number of class attendance affect student mid-term exam score?	●	●	**Causal relationship**
2. What is the relationship between students' quiz score and their test score?	●	●	**Forecast student's score based on independent variables**
3. With a regression formula: *final exam score = 20 + 0.60 x class attendance,* what is the effect on the final exam score every time a student misses a class?	●	●	**Understand the correlation relation between two variables**
4. Give a regression formula: *test score = 15 + 0.85 x homework score* , what is the test score that a student is likely to get if she gets 90 for her homework?	●	●	**Inferential statistical t-test**
5. Is there a significant difference of average math test score between two school classes?	●	●	**Predicting trends in student score based on change in independent variable(s)**

4.3 Following the previous question, if your goal is to know how each learning activity is likely to affect student final exam score, which of the following actions would you take? (select all that apply)

- ☐ 1. Run a correlation analysis on students' scores on all learning activities
- ☐ 2. Run a regression analysis by using learning activities scores to predict the final exam scores
- ☐ 3. Check statistical significance and compare coefficients to see how each learning activity contributes to final exam score
- ☐ 4. Check statistical significance on each correlation coefficient between any of the two learning activities
- ☐ 5. Identify the direction and strength of each correlation coefficient
- ☐ 6. Identify the direction and strength of each regression coefficient

5. Please circle only one answer for each of the following questions:

(1) I can assess student performances in the classroom

Disagree 1 2 3 4 5 6 7 Agree

(2) I can adapt my teaching based upon what students currently understand or do not understand

Disagree 1 2 3 4 5 6 7 Agree

(3) I can adapt my teaching style to different learners

Disagree 1 2 3 4 5 6 7 Agree

(4) I can assess student learning in multiple ways

Disagree 1 2 3 4 5 6 7 Agree

(5) I can use a wide range of teaching approaches in a classroom setting

Disagree 1 2 3 4 5 6 7 Agree

(6) I am familiar with common student understandings and misconceptions

Disagree 1 2 3 4 5 6 7 Agree

6. Please circle only one answer for each of the following questions:

(1) Do you feel you can choose technologies that enhance your teaching approaches for a lesson?

Disagree 1 2 3 4 5 6 7 Agree

(2) Do you feel you can choose technologies to enhance students' learning for a lesson?

Disagree 1 2 3 4 5 6 7 Agree

(3) Do you feel you can think critically about how to use technology in your future classroom?

Disagree 1 2 3 4 5 6 7 Agree

(4) Do you feel you can adapt different technologies to different teaching activities?

Disagree 1 2 3 4 5 6 7 Agree

7. Please circle only one answer for each of the following questions:

(1) To what extent can you use a variety of assessment strategies?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(2) To what extent can you provide an alternative explanation or example when students are confused?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(3) To what extent can you craft good questions for your students?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(4) How well can you implement alternative strategies in your classroom?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(5) How much can you do to control disruptive behavior in the classroom?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(6) How much can you do to get children to follow classroom rules?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(7) How much can you do to calm a student who is disruptive or noisy?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(8) How well can you establish a classroom management system with each group of students?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(9) How much can you do to get students to believe they can do well in school?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(10) How much can you do to help your students value learning?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(11) How much can you do to motivate students who show low interest in school?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(12) How much can you assist families in helping their children do well in school?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

8. Please circle only one answer for each of the following questions:

(1) When I make plans I follow through with them

Disagree 1 2 3 4 5 6 7 Agree

(2) I usually manage one way or another

Disagree 1 2 3 4 5 6 7 Agree

(3) I am able to depend on myself more than anyone else

Disagree 1 2 3 4 5 6 7 Agree

(4) Keeping interested in things is important to me

Disagree 1 2 3 4 5 6 7 Agree

(5) I can be on my own if I have to

Disagree 1 2 3 4 5 6 7 Agree

(6) I feel proud that I have accomplished things in my life

Disagree 1 2 3 4 5 6 7 Agree

(7) I usually take things in stride

Disagree 1 2 3 4 5 6 7 Agree

(8) I am friends with myself

Disagree 1 2 3 4 5 6 7 Agree

(9) I feel that I can handle many things at a time

Disagree 1 2 3 4 5 6 7 Agree

(10) I am determined

Disagree 1 2 3 4 5 6 7 Agree

(11) I seldom wonder what the point of it all is

Disagree 1 2 3 4 5 6 7 Agree

(12) I take things one day at a time

Disagree 1 2 3 4 5 6 7 Agree

(13) I can get through difficult times because I've experienced difficulty before

Disagree	1	2	3	4	5	6	7	Agree

(14) I have self-discipline

Disagree	1	2	3	4	5	6	7	Agree

(15) I keep interest in things

Disagree	1	2	3	4	5	6	7	Agree

(16) I can usually find something to laugh about

Disagree	1	2	3	4	5	6	7	Agree

(17) My belief in myself gets me through hard times

Disagree	1	2	3	4	5	6	7	Agree

(18) In an emergency, I am someone people generally can rely on

Disagree	1	2	3	4	5	6	7	Agree

(19) I can generally look at a situation in a number of ways

Disagree	1	2	3	4	5	6	7	Agree

(20) Sometimes I make myself do things whether I want to or not

Disagree	1	2	3	4	5	6	7	Agree

(21) My life has meaning

Disagree	1	2	3	4	5	6	7	Agree

(22) I do not dwell on things that I can't do anything about

Disagree	1	2	3	4	5	6	7	Agree

(23) When I am in a difficult situation, I can usually find my way out of it

Disagree	1	2	3	4	5	6	7	Agree

(24) I have enough energy to do what I have to do

Disagree	1	2	3	4	5	6	7	Agree

(25) It's okay if there are people who don't like me

Disagree	1	2	3	4	5	6	7	Agree

End of this survey, thank you!

Appendix D

Learning Analytics Activity

Learning Analytics Activity —
Examine Students' Performance on Various Math Learning Activities

Imagine you are an elementary school math teacher. Your teacher colleague Megan, who is also teaching elementary math, has recently been introduced to a Learning Management System (LMS)[1] at school through professional development. She is motivated to use students' learning data on the LMS to gain insights into students' learning outcomes. To experiment with this idea, Megan has collected students' data on various learning activities of a few mathematical concepts she has taught to her class, including quizzes, assignments, and tests.

Although Megan is excited about the insights that students' learning data may bring on this LMS system, she is trying to understand how the different learning activities she designs help students learn different math concepts. Megan wants to know how you find out your teaching skills, and students' learning outcomes?

Please let the experimenter know when you finish reading the information on this page

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[1] LMS is a digital learning management system such as Google Classroom, Canvas, or Class Dojo.

Appendix E

Interview Questions

1. **Can you mention 3 things you think most relevant to your teaching about today's tutorial?**

2. **Based on what you learn today about (weekly subject names), can you give me an example about how you will use it in your teaching?**

3. **On the scale from 1 to 5, how important is this week's tutorial content to your teaching and why?**

Appendix F

Getting Familiar with Student Data

1) **Please open the Microsoft Excel file that the experimenter shares with you and make sure you can see the content. There are several tabs at the bottom of that Excel file, which you will use throughout this tutorial:**
    - tab1_raw_data
    - tab2_mean
    - tab3_median
    - tab4_variance(1)
    - tab5_variance(2)

Your colleague Megan has been teaching a few mathematical concepts to her students. She also has collected several student scores on various learning activities. She has shared these learning data with you.

2) **First, please click on the first tab (tab1_raw_data), and take a look at the data as well as each column. You can see the definition of each variable column below:**
    - student_id: unique identifier for each student in this class
    - gender: student's gender
    - group: learning group that each student is assigned to in this class
    - ratios_quiz1: student's grade of the first quiz on ratios
    - ratios_quiz2: student's grade of the second quiz on ratios
    - rates_quiz1: student's grade of the first quiz on rates
    - rates_quiz2: student's grade of the second quiz on rates
    - percents_quiz1: student's grade of the first quiz on percents
    - percents_quiz2: student's grade of the second quiz on percents
    - ratios_assignment: student's assignment grade on ratios
    - rates_assignment: student's assignment grade on rates
    - percents_assignment: student's assignment grade on percents
    - ratios_test: student's test grade on ratios
    - rates_test: student's test grade on rates
    - percents_test: student's test grade on percents

Now Megan wants to know the mean score for each of the learning activities that her students have finished. She also wants to compare these mean scores across the 3 different math concepts she has taught to her students.

Calculate mean for student quiz, assignment, and test score

NOTE: Mean is a value that represents an average of an array of numbers. To calculate a mean value, you will add the numbers together and divide it by the total count of numbers supplied. For example, the mean of (2,4,6) will be 4.

1) **Click on the second tab(tab2_mean). In this tab, you will calculate the mean for students' average scores of their quizzes, assignments, and tests for each mathematical concepts: ratios, rates, percents**

2) **You will need to calculate different mean values and put them in specific cells. For instance, in the following, "Mean for ratios quiz 1 & 2 scores (Q2)" suggests that you will need to calculate mean for two ratios quizzes and put it in the Q2 cell. The nine mean values that need to be calculated are:**

   - Mean for ratios quiz 1 & 2 scores
   - Mean for rates quiz 1 & 2 scores
   - Mean for percents quiz 1 & 2 scores
   - Mean for ratio assignment score
   - Mean for rates assignment score
   - Mean for percents assignment score
   - Mean for ratios test score
   - Mean for rates test score
   - Mean for percents test score

3) **To get the mean for ratios quiz 1 & 2 scores, click on cell Q2, and in the formula function box at the top, enter =AVERAGE(D2:E22), which indicates the range of cells required to calculate this mean value. Afterwards, hit 'enter' and you should be seeing a mean value for ratios quiz 1 & 2 scores.**

4) **Similarly, You can get the mean for ratio assignment score and ratio test score R2 and S2 by using the =AVERAGE() function and select appropriate data range**

5) **Now, using the same approach and calculate the remaining mean values**

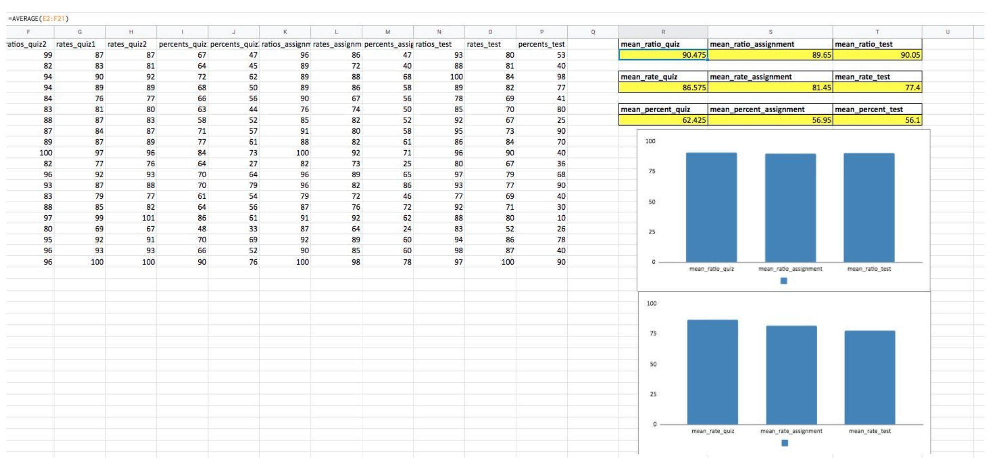
6) **Now you have 9 different mean scores, which represent students' average performance for each learning activity (i.e. quiz, assignment, test) for each mathematical concept (ratio, rates, percents). Take a moment to compare these mean scores and summarize your findings on the note paper. What kind of information will you report to your colleague Megan?**

7) **Next, you will visualize these mean values by using bar chart. Bar chart helps you see the difference in scores and patterns more intuitively. For example, to create a bar chart for quiz, assignment, and test score for the math concept of ratio, you can do the following:**

1. Select all the column name and data, that means select from **Q2** to **S2**

2. Click on **'Insert'** and select **'Chart'** and **'Column'** at the top of the page on the toolbar

3. After finishing the previous steps, you should see the bar chart. Feel welcome to modify the layout and details of the bar chart by using clicking on the chart, and then under **'Chart Design'** select **'Quick Layouts'** under on the toolbar, and editing the details of your chart.


=AVERAGE(E2:F21)

ratios_quiz2	rates_quiz1	rates_quiz2	percents_quiz	percents_quiz	ratios_assignm	rates_assignm	percents_assig	ratios_test	rates_test	percents_test
99	87	87	67	47	96	86	47	93	80	53
82	83	81	64	45	89	72	40	88	81	40
94	90	92	72	62	89	88	68	100	84	98
94	89	89	68	50	89	86	58	89	82	77
84	76	77	66	56	90	67	56	78	69	41
83	81	80	63	44	76	74	50	85	70	80
88	87	83	58	52	85	82	52	92	67	25
87	84	87	71	57	91	80	58	95	73	90
89	87	89	77	61	88	82	61	86	84	70
100	97	96	84	73	100	92	71	96	90	40
82	77	76	64	27	82	73	25	80	67	36
96	92	93	70	64	96	89	65	97	79	68
93	87	88	70	79	96	82	86	93	77	90
83	79	77	61	54	79	72	46	77	69	40
88	85	82	64	56	87	76	72	92	71	30
97	99	101	86	61	91	92	62	88	80	10
80	69	67	48	33	87	64	24	83	52	26
95	92	91	70	69	92	89	60	94	86	78
96	93	93	66	52	90	85	60	98	87	40
96	100	100	90	76	100	98	78	97	100	90

mean_ratio_quiz	mean_ratio_assignment	mean_ratio_test
90.475	89.65	90.05
mean_rate_quiz	mean_rate_assignment	mean_rate_test
86.575	81.45	77.4
mean_percent_quiz	mean_percent_assignment	mean_percent_test
62.425	56.95	56.1

8) **Following the same approach, you can continue to create two more bar charts for the math concept of rates and percents. Please let your partner know if you have trouble finishing this.**

9) **Your colleague Megan has informed you that student No.21 is a new student that has just transferred from another school. She wants to know how this new student's mean scores compares to the class on different learning activities, please share with your partner how would you analyze it?**

Next, Megan wants to know the median score for each of the learning activities. She wants to compare these median scores across the 3 different math concepts she has taught to her students.

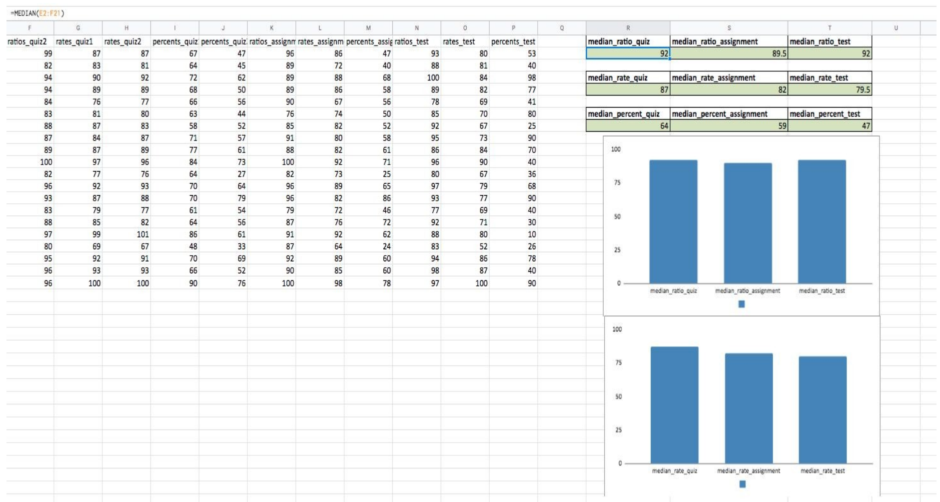
Calculate median for student quiz, assignment, and test score

NOTE: **Median is a value that represents another type of average of an array of numbers. It is the middle number in an array of supplied numbers. For example, the median of (1,2,3,4,5) will be 3. On the other hand, if the total count of numbers in the array is an even number, such as (1,4,3,2), then the median will be the mean of the two middle numbers. In this case, the median will be (2+3)/2 = 2.5**

1) **To calculate the median scores for each learning activity and each math concept, you can click on the third tab (tab3_median), and you should see a similar template for student scores as in the previous exercise.**

2) **Now you need to calculate 9 different median values. To do so, click Q2, and in the formula function box at the top, use MEDIAN(.) function and select appropriate data range, and hit 'enter'. Following the same approach, calculate the rest of the median scores using the MEDIAN(..) function.**

3) **As you are updating these median values, you should also see their associated bar charts changing accordingly below the table.**



ratios_quiz2	rates_quiz1	rates_quiz2	percents_quiz	percents_quiz	ratios_assignm	rates_assignm	percents_assig	ratios_test	rates_test	percents_test
99	87	87	67	47	96	86	47	93	80	53
82	83	81	64	45	89	72	40	88	81	40
94	90	92	72	62	89	88	68	100	84	98
94	89	89	68	50	89	86	58	89	82	77
84	76	77	66	56	90	67	56	78	69	41
83	81	80	63	44	76	74	50	85	70	80
88	87	83	58	52	85	82	52	92	67	25
87	84	87	71	57	91	80	58	95	73	90
89	87	89	77	61	88	82	61	86	84	70
100	97	96	84	73	100	92	71	96	90	40
82	77	76	64	27	82	73	25	80	67	36
96	92	93	70	64	96	89	65	97	79	68
93	87	88	70	79	96	82	86	93	77	90
83	79	77	61	54	79	72	46	77	69	40
88	85	82	64	56	87	76	72	92	71	30
97	99	101	86	61	91	92	62	88	80	10
80	69	67	48	33	87	64	24	83	52	26
95	92	91	70	69	92	89	60	94	86	78
96	93	93	66	52	90	85	60	98	87	40
96	100	100	90	76	100	98	78	97	100	90

median_ratio_quiz	median_ratio_assignment	median_ratio_test
92	89.5	92

median_rate_quiz	median_rate_assignment	median_rate_test
87	82	79.5

median_percent_quiz	median_percent_assignment	median_percent_test
64	59	47

4) **After you are done, take a minute to observe these median values and also compare them with the mean values you have previously calculated and plotted. What kind of information would you like to share with Megan?**

5) **Megan wants to know how median works. Take the percents test score for example, can you explain to Megan how the function =MEDIAN() works when you used it to get the median for the percents test score?**

6) **Similarly, Megan is wondering if the function =MEDIAN() will work differently if one student score is missing from the percents test column. Can you explain it to her?**

7) **Lastly, when Megan looks at your visualizations for mean and median, she has found that there is a large difference in the percent test score when you used mean versus median to calculate the average. Can you explain to Megan why this is the case?**

____ End of week 1 tutorial ____

Appendix G

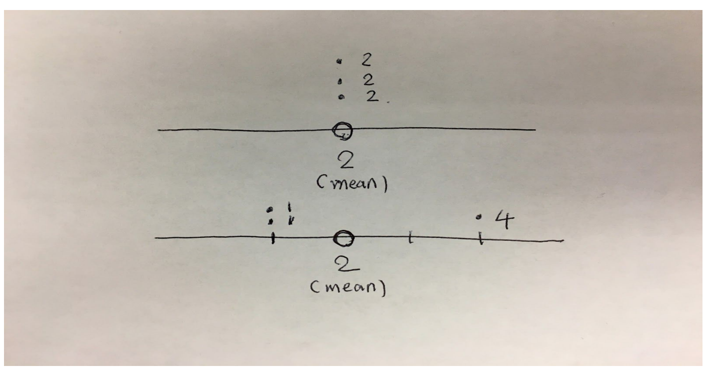
Week 2: Tutorial

Your colleague Megan has taught a few mathematical concepts to her students. She has also collected several student scores on various learning activities. Last week you helped Megan to understand the mean and median of her students' scores. This week she needs your help with other data analytics questions.

Megan wants to know the variance of the test scores for all three math concepts: ratio, rate, and percent. She has taught these three concepts to her students and her students have taken those tests.

Calculate variance for ratios, rates, and percents test scores

<u>NOTE:</u> Variance in statistics is a measurement of the spread between numbers in a data array. It measures how far each number in a number set is from their collective mean in that number set. For example, the two number arrays (1, 1, 4) and (2, 2, 2) both have the same mean value of 2, but the first number array has a larger variance since each number spread from their collective mean more in the first array than in the second array. Here is a visualization and the formula for variance to help you understand:



The Formula for Variance Is

$$\text{variance } \sigma^2 = \frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{n}$$

where:

$x_i =$ the i^{th} data point

$\bar{x} =$ the mean of all data points

$n =$ the number of data points

1) **You will practice calculating variance for test score on each math concept (ratios, rates, percents). Please click on the fourth tab (tab4_variance(1)), where you can see in cell Q2, R2, and S2 you will need to calculate the variance for each test.**

2) **To calculate the variance value for the ratio test score, click on Q2, and in the formula function box at the top type in =VAR(M2:M21) and then hit 'enter'.**

3) **Similarly, please finish calculating the variance value for rate test (R2) and percent test (S2) by using the same =VAR(...) function and selecting their corresponding data range.**

Megan wants to know how the VAR(...) function works in Excel. Can you explain to Megan that what are the steps that Excel takes to get the variance for a test score?

4) **Take a moment to observe different variance values across three different tests. Summarize your findings on the note paper.**

5) **Oftentimes, we will want to know mean and variance for a test score at the same time, so that we know not only the average performance on that test, but also how similarly or differently students perform on that test. Since variance can't be plotted directly with the mean, we will use standard deviation, which is just the square root of the variance. For example, if the variance of a test score is 9, then its standard deviation is $\sqrt{9} = 3$.**

Megan thinks it is not very useful to know only the variance, and she wants to see both mean and standard deviation at the same time. Next, let's try to plot both on the same graph.

6) **To do so, click on tab5_variance(2), and first you need to calculate the mean value for the three tests as you have done previously by using =AVERAGE(...). Fill in Q2, R2, and S2 cells with mean value for each test score. Please let your partner know if you have questions.**

7) To visualize both the mean and standard deviation across the three tests, you will need to plot a bar chart that shows 3 mean values. You have done this previously, just to review, here are the steps:

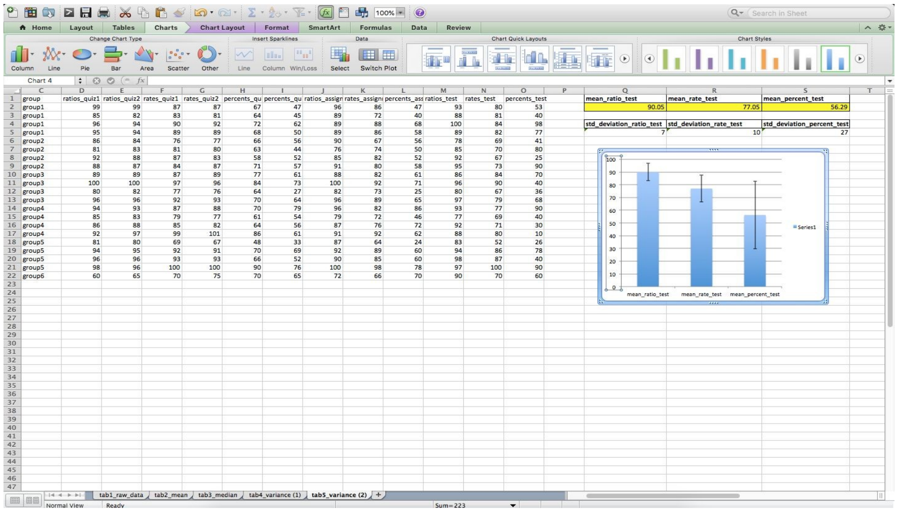
1. Select all the column name and data, that means select from **Q1** to **S2**

2. Click on **'Insert'** and **'Chart'**, and' select **'Column'** at the top of the page on the toolbar

3. After finishing the previous steps, you should see the bar chart. Feel welcome to modify the layout and details of the bar chart by using **Chart Design' and 'Quick Layouts'**.

8) After you have plotted the bar chart that shows three mean values for all the tests, you can add the standard deviation onto the same bar chart. Standard deviation is just the square root of the variance. The standard deviation for each math concept has been pre-calculated from Q5 to S5 cell for you.

9) To add standard deviation on the bar plot, first click on the bar chart you have created, then on the top click on 'Chart Design' and 'Add Chart Element'. Click on 'Error Bars' and choose the last option 'Error Bars Options'. Afterwards, choose 'Custom' and click on 'Specify Value'. In both boxes where it says 'Positive Error Value' and 'Negative Error Value', click on the small colorful windows next to them and select cell Q5 to S5 in this Excel tab. Click 'OK' and you should see standard deviation added on to the mean values(see image below).



10) **After you are done, take a minute to observe and compare the mean and standard deviation value across the three math tests. What kind of information would you like to share with Megan?**

11) **Megan wants to know what it means to have high standard deviation(variance), take a look at a test score, and explain to Megan.**

12) **Megan wants to know what she should do? What would you say?**

Megan appreciates all the data analytics insights you provided. Now she is interested in investigating another dataset which has students' data from another class she teaches.

Investigate dataset from Megan's 2nd class

1) **Please open the Microsoft Excel file that the experimenter shares with you and make sure you can see the content. There are several tabs at the bottom of that Excel file, which you will use throughout this tutorial:**
   - tab1_raw_data
   - tab2_correlation
   - tab3_correlation(2)
   - tab4_correlation(3)
   - tab5_regression
   - tab6_regression_prediction

2) **First, please click on the first tab (tab1_raw_data), and take a look at the data as well as each column. You can see the definition of each variable column below:**
    - student_id: unique identifier for each student in this class
    - gender: student's gender
    - quiz1_ratio: student's quiz 1 score
    - quiz2_percent: student's quiz 2 score
    - assignment1_ratio: student's assignment 1 score
    - assignment2_geometry: student's assignment 2 score
    - exam_score: student's exam score

Megan wants to know the correlation relations between different learning activities.

Calculate correlation coefficients between different learning activities

NOTE: We use correlation coefficient (a value between -1 and 1) to display how strongly two variables are related to each other, but not to use one to predict the other. If the correlation coefficient is positive between two variables, that means there is a positive relationship between the two variables. This means if one goes up the other goes up, too. In contrast, if the correlation coefficient is negative, then that means there is a negative relationship between the two variables. This means if one goes up, the other goes down. The strength of correlation coefficient is indicated by the coefficient value, below is a convention to define correlation strength:

- Exactly - 1: A perfect negative correlation
- - 0.70: A strong negative correlation
- - 0.50: A moderate negative correlation
- - 0.30: A weak negative correlation
- 0: No correlation relationship
- + 0.30: A weak positive correlation
- + 0.50. A moderate positive correlation
- + 0.70. A strong positive correlation
- Exactly + 1: A perfect positive correlation

1) You will use Excel to calculate correlation coefficients, which will give you some insights into the relationship between different learning activities.   To examine the correlation between different learning activities, click on tab2 (tab2_correlation)

2) On the right-hand side of the excel page, you will see a table in which you will calculate and fill in different correlation coefficients.

student_id	quiz1	quiz2	assignment1	assignment2	exam_score
quiz1	1				
quiz2		1			
assignment1			1		
assignment2				1	
exam_score					1

3) You will notice that the diagonal is filled up with the value 1. This makes sense because correlation coefficient 1 suggests perfect positive correlation between a variable and the variable itself. In other words, quiz1 scores positively correlates with itself perfectly. However, to get correlation coefficients between different learning activities, you will need to use the Excel function =CORREL(.   )

4) For example, to get the correlation coefficient between quiz 1 and quiz 2, you need to first click on cell J5, then click on the formula icon next to the *fx* at the top on the toolbar, then type =CORREL(. ....). You should then see an image like this:

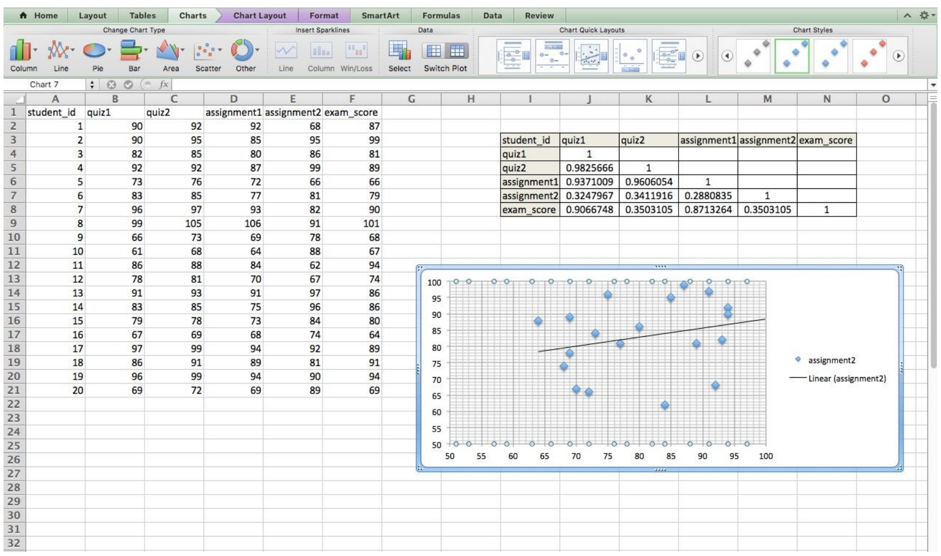
5) To get the correlation coefficient between quiz 1 & quiz 2, you will need to select their data range separately. For correlation between quiz 1 and quiz 2, you need to select B2:B21 select C2:C21. So the final formula should be =CORREL(B2:B21, C2:C21).In the end, hit 'enter' key and then you should see the correlation coefficient 0.98 between quiz 1 & 2. This suggests there is a strong positive correlation between the two. In other words, students that do well on quiz 1 are also likely to do well on quiz 2.

6) Now, repeat the same procedure and calculate all other correlation coefficients between different learning activities. For each of the remaining

empty cell in the correlation table, remember to select their corresponding data range. Please note, you will only need to fill out the rest of the cells below the diagonal numbers of 1.

Megan is impressed by the correlation table you created, but she wants to summarize it, what would you do?

7) **In the end, you can also visualize correlation between any two learning activities. For example, to visualize correlation between assignment 1 and assignment 2, click and select both column D and E which correspond to their data range(use command key to select both columns). Then, on the toolbar, click on Insert, Charts, and choose X Y Scatter. After the scatter plot pops up, you can also adjust the details and layout under Chart Design and using Add Chart Element. For instance, you can add a linear trend line under Trendline In the end, you should see an image that is similar to the one in the following:**



student_id	quiz1	quiz2	assignment1	assignment2	exam_score
1	90	92	92	68	87
2	90	95	85	95	99
3	82	85	80	86	81
4	92	92	87	99	89
5	73	76	72	66	66
6	83	85	77	81	79
7	96	97	93	82	90
8	99	105	106	91	101
9	66	73	69	78	68
10	61	68	64	88	67
11	86	88	84	62	94
12	78	81	70	67	74
13	91	93	91	97	86
14	83	85	75	96	86
15	79	78	73	84	80
16	67	69	68	74	64
17	97	99	94	92	89
18	86	91	89	81	91
19	96	99	94	90	94
20	69	72	69	89	69

student_id	quiz1	quiz2	assignment1	assignment2	exam_score
quiz1	1				
quiz2	0.9825666	1			
assignment1	0.9371009	0.9606054	1		
assignment2	0.3247967	0.3411916	0.2880835	1	
exam_score	0.9066748	0.3503105	0.8713264	0.3503105	1

8) **After you are done, click on tab3_correlation(2), you will see two correlation plots about quiz 1, assignment 1 and 2. What kind of information would you like to share with Megan?**

9) On the other hand, Megan has done a survey to ask students about their weekly average sleep time (hours) and shared the data with you in tab4_correlation(3). She plotted the students' sleep time and their exam scores. She realized that there is a high correlation (r=+0.91) between the two. She wants to know how would you explain this result?

____ End of week 2 tutorial ____

Appendix H

Week 2: Survey

Your name (for data analysis purpose only): ____________________

1. Please circle only one answer for each of the following questions:

(1) I can assess student performances in the classroom

Disagree 1 2 3 4 5 6 7 Agree

(2) I can adapt my teaching based upon what students currently understand or do not understand

Disagree 1 2 3 4 5 6 7 Agree

(3) I can adapt my teaching style to different learners

Disagree 1 2 3 4 5 6 7 Agree

(4) I can assess student learning in multiple ways

Disagree 1 2 3 4 5 6 7 Agree

(5) I can use a wide range of teaching approaches in a classroom setting

Disagree 1 2 3 4 5 6 7 Agree

(6) I am familiar with common student understandings and misconceptions

Disagree 1 2 3 4 5 6 7 Agree

2. Please circle only one answer for each of the following questions:

(1) Do you feel you can choose technologies that enhance your teaching approaches for a lesson?

Disagree 1 2 3 4 5 6 7 Agree

(2) Do you feel you can choose technologies to enhance students' learning for a lesson?

Disagree 1 2 3 4 5 6 7 Agree

(3) Do you feel you can think critically about how to use technology in your future classroom?

Disagree 1 2 3 4 5 6 7 Agree

(4) Do you feel you can adapt different technologies to different teaching activities?

Disagree 1 2 3 4 5 6 7 Agree

3. Please circle only one answer for each of the following questions:

(1) To what extent can you use a variety of assessment strategies?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(2) To what extent can you provide an alternative explanation or example when students are confused?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(3) To what extent can you craft good questions for your students?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(4) How well can you implement alternative strategies in your classroom?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(5) How much can you do to control disruptive behavior in the classroom?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(6) How much can you do to get children to follow classroom rules?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(7) How much can you do to calm a student who is disruptive or noisy?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(8) How well can you establish a classroom management system with each group of students?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(9) How much can you do to get students to believe they can do well in school?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(10) How much can you do to help your students value learning?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(11) How much can you do to motivate students who show low interest in school?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(12) How much can you assist families in helping their children do well in school?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

4. Please circle only one answer for each of the following questions:

(1) When I make plans I follow through with them

Disagree 1 2 3 4 5 6 7 Agree

(2) I usually manage one way or another

Disagree 1 2 3 4 5 6 7 Agree

(3) I am able to depend on myself more than anyone else

Disagree 1 2 3 4 5 6 7 Agree

(4) Keeping interested in things is important to me

Disagree 1 2 3 4 5 6 7 Agree

(5) I can be on my own if I have to

Disagree 1 2 3 4 5 6 7 Agree

(6) I feel proud that I have accomplished things in my life

Disagree 1 2 3 4 5 6 7 Agree

(7) I usually take things in stride

Disagree 1 2 3 4 5 6 7 Agree

(8) I am friends with myself

Disagree 1 2 3 4 5 6 7 Agree

(9) I feel that I can handle many things at a time

Disagree 1 2 3 4 5 6 7 Agree

(10) I am determined

Disagree 1 2 3 4 5 6 7 Agree

(11) I seldom wonder what the point of it all is

Disagree	1	2	3	4	5	6	7	Agree

(12) I take things one day at a time

Disagree	1	2	3	4	5	6	7	Agree

(13) I can get through difficult times because I've experienced difficulty before

Disagree	1	2	3	4	5	6	7	Agree

(14) I have self-discipline

Disagree	1	2	3	4	5	6	7	Agree

(15) I keep interest in things

Disagree	1	2	3	4	5	6	7	Agree

(16) I can usually find something to laugh about

Disagree	1	2	3	4	5	6	7	Agree

(17) My belief in myself gets me through hard times

Disagree	1	2	3	4	5	6	7	Agree

(18) In an emergency, I am someone people generally can rely on

Disagree	1	2	3	4	5	6	7	Agree

(19) I can generally look at a situation in a number of ways

Disagree	1	2	3	4	5	6	7	Agree

(20) Sometimes I make myself do things whether I want to or not

Disagree	1	2	3	4	5	6	7	Agree

(21) My life has meaning

Disagree	1	2	3	4	5	6	7	Agree

(22) I do not dwell on things that I can't do anything about

Disagree	1	2	3	4	5	6	7	Agree

(23) When I am in a difficult situation, I can usually find my way out of it

Disagree	1	2	3	4	5	6	7	Agree

(24) I have enough energy to do what I have to do

Disagree	1	2	3	4	5	6	7	Agree

(25) It's okay if there are people who don't like me

Disagree	1	2	3	4	5	6	7	Agree

End of this survey, thank you!

Appendix I

Week 3: Tutorial

Your colleague Megan has taught a few mathematical concepts to her students. She has also collected several student scores on various learning activities. So far you have helped Megan to understand the mean, median, variance, and correlation of her students' scores of different learning activities. This week she needs your help with other data analytics questions.

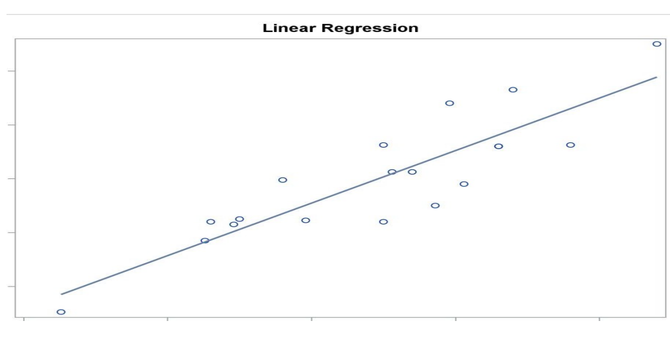
Last week, we discussed the example of the relation between students' sleep time and exam score. There was a positive correlation between sleep more and score higher on the example. However, correlation does not assume the direction or contribution of one factor to the other between sleep time and exam score. It simply just describes the relation between the two. Using regression will help us see how one thing contributes to the other.

Megan wants to know how to use regression to check how each learning activity contributes to the final exam score

Fit a regression model

<u>NOTE:</u> Using regression analysis can help us examine how each learning activity(input variable) contributes to the output variable(final exam). Regression analysis is also useful to tell us the importance of each learning activity in terms of their contribution to the final exam score. For instance, if we fit a regression model between an assignment (input variable) and exam score (output variable) in the following:

Exam score



Assignment score

Exam score = 0.9 x Assignment score

There are two things to pay attention to when we interpret a regression model. The first thing is the coefficient of the input variable(Assignment score). In our example, the coefficient is 0.9. The value of 0.9 is the contribution that assignment score can make to the Exam score. Larger the coefficient, larger that contribution. In other words, in this example, if a student scores 80 points on the Assignment, that student is likely to score 72 points (80 x 0.9=72) based on this regression model.

The second thing to notice about regression model is the P-value of the coefficient of a learning activity. P-value suggests statistical significance of the contribution of a learning activity to the exam score. By convention, if the P-value is under 0.05 ($p < 0.05$), then we will say the coefficient (contribution) is valid and we can trust the result with 95% confidence. 95% confidence means out of 100 times we run this regression model, 95 out of 100 times we will get a coefficient value that is very close to the coefficient the regression model gives us.

Please let your partner know if you have questions about this example.

1) **Click on tab5(tab5_regression), at this step you will use Excel to fit a regression model to examine the relation between different learning activities and the final exam score.**

2) **Click on Data on the toolbar at the top of the page, under Data Analysis search and choose Regression function. In the input box, you need to specify input Y range (final exam score) and input X range (quiz1&2, and assignment 1&2). For input Y range, select data range F1:F21 including the column name. For input X range, select data range B1:E21 including their column names.**

3) **Check the ‘Label’ box, and click on ‘OK’, you should see the following output:**

student_id	quiz1	quiz2	assignment1	assignment2	exam_score
1	85	91	90	89	90
2	86	83	86	89	90
3	79	80	82	82	84
4	92	83	90	90	93
5	67	71	70	74	74
6	78	83	81	83	84
7	93	91	90	95	95
8	97	99	98	101	100
9	65	66	66	64	66
10	60	53	58	63	63
11	81	88	89	86	88
12	77	78	81	78	79
13	93	88	87	91	92
14	79	80	81	84	84
15	78	79	76	81	81
16	66	60	68	65	68
17	92	95	98	96	99
18	87	82	84	85	87
19	88	85	96	94	95
20	66	67	68	72	71

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.998111555
R Square	0.996226675
Adjusted R Sq	0.995220456
Standard Err	0.755268328
Observations	20

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	2259.060213	564.76505	990.06856	5.668E-18
Residual	15	8.556453705	0.5704302		
Total	19	2267.616667			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.674116123	1.351457645	1.2387485	0.2344739	-1.206448	4.5546799	-1.206448	4.5546799
quiz1	0.167427166	0.061573515	2.7191426	0.0158386	0.0361863	0.298668	0.0361863	0.298668
quiz2	-0.014431767	0.055130556	-0.261774	0.7970559	-0.13194	0.1030762	-0.13194	0.1030762
assignment1	0.267315403	0.063927669	4.181529	0.0008023	0.1310568	0.403574	0.1310568	0.403574
assignment2	0.580295093	0.085479371	6.788715	6.109E-06	0.3981001	0.7624901	0.3981001	0.7624901

Megan wants to know how to interpret the results. She has found that in the results quiz1, quiz2, assignment1, and assignment2 have different coefficients and P-value.

<u>NOTE:</u> The way to explain coefficients is to examine their direction, slope, and p-value. For example, quiz 1's coefficient is 0.16 while quiz 2 is -0.01. This means their contribution on the exam score is different regarding both the direction and strength. Also, if you check the P-value for both coefficients, you will find for quiz 1 is 0.01 while for quiz 2 is 0.79. By convention, P-value has to be lower than 0.05 ($p < 0.05$) for a coefficient to be called significant. So in this case, we will say the coefficient for quiz 2 is NOT significant so we can't trust its contribution to the exam score.

Megan has written down the regression model you have helped her build in the following:
*exam score = (0.16 * quiz 1) + (-0.01 * quiz 2) + (0.26 * assignment 1) + (0.58 * assignment 2)*

a. **Take a look at the results in the Excel sheet and the NOTE about coefficients above, how would you explain to Megan the effect of each learning activity regarding their contribution to the exam score?**

b. **In the end, Megan has decided to remove quiz 2 from this regression model, why do you think she did that?**

c. **What would you suggest Megan do based on this regression model and results?**

Megan has understood the effect of each learning activity regarding their contribution to students' exam scores. Since she wants to predict exam scores for other students who have finished all the learning activities but have not taken the exam.

Use regression model predict students at-risk

<u>NOTE:</u> Regression model has another function: prediction. After we establish a regression model using some data, we can use that model to predict the future outcome. For instance, after removing the quiz 2 in the regression model, we can use only quiz 1, assignment 1, and assignment 2 as the input variables and exam score as the output variable. The new regression model using these variable will be the following:

*exam score=0.17 * quiz 1 + 0.26 * assignment 1 + 0.57 * assignment 2*

Now if we have a new student coming in the class who has finished quiz 1 and assignment 1 & 2, and received scores of 90,92, and 68 for these activities.
If we want to predict how well (s)he is going to do on the exam, we can plug in the three learning activities scores into the regression formula and we will get a predicted exam score. For instance, we can do the following:

*New student's predicted exam score = 0.17 * (90) + 0.26 * (92) + 0.57* (68) =78*

Therefore, the predicted exam score for this student will be 78. You can verify this answer with your calculator or using Excel.

Megan wants to use the regression model to predict several other students' exam scores.

1) **Click on tab6(tab6_regression_prediction). In this tab you will see 10 new students and their scores for quiz 1 and assignment 1 & 2. You will also see in the function box at the top the regression formula from the previous step has been supplied. Take a look at formula and students' data in this tab.**

2) **To predict their exam scores, you can supply the three learning activity scores into a regression formula. If you click on cell E2,**

you will find that all the activity scores for the first student have been supplied into the formula and there is a predicted exam score for this student already.

A	B	C	D	E
student_id	quiz1	assignment1	assignment2	exam_score
21	90	92	68	78.0
22	90	85	95	
23	80	80	86	
24	90	87	99	
25	75	72	90	
26	83	77	60	
27	70	93	82	
28	100	100	91	
29	65	69	78	
30	61	64	88	

3) **To get the rest of the predicted exam scores for the other 9 students, simply click on the bottom right corner of cell E2, and then drag all the way down to the bottom of E11. You should see all empty cells in the exam_score column being filled out with a predicted score for each student.**

A	B	C	D	E
student_id	quiz1	assignment1	assignment2	exam_score
21	90	92	68	78.0
22	90	85	95	91.6
23	80	80	86	83.4
24	90	87	99	94.4
25	75	72	90	82.8
26	83	77	60	68.3
27	70	93	82	82.8
28	100	100	91	94.9
29	65	69	78	73.5
30	61	64	88	77.2

4) **After you are done, take a moment to observe the predicted exam scores. Megan wants to know If the passing grade is 80, which students are likely to fail the exam based on the prediction this regression model makes?**

5) **If you take a look at the contribution of each learning activity to the exam score, what would you suggest Megan do?**

____ **End of week 3 tutorial** _____

Appendix J

Week 3: Posttest Survey

Your name (for data analysis purpose only): ____________________

Data Analytics Knowledge Questions

1.1 To get a sense of students' average performance, you can calculate median. Given two student groups' scores below, please write down your calculation process and the median for each group below:

Group 1 scores: (70, 50, 97, 83)
Group 2 scores: (100, 40, 55, 80)

Please put your calculation process here:

Group 1 median: _____________
Group 2 median: _____________

1.2 To get a sense of students' average performance, you can also calculate mean. Given the same student scores as in the previous question, please write down the mean for each group below:

Group 1 scores: (70, 50, 97, 83)
Group 2 scores: (100, 40, 55, 80)

Please put your calculation process here:

Group 1 mean: _____________
Group 2 mean: _____________

1.3 If there you remove the smallest number from each of the two group scores, what is the new mean for each group?

Group 1 scores: (60, 77, 55, 97, 81)
Group 2 scores: (88, 42, 30, 95, 100)

Please put your calculation process here:

Group 1 mean: _____________
Group 2 mean: _____________

1.4 If there is a new score 88 to be added into each of the two group scores, what is the new median for each group?

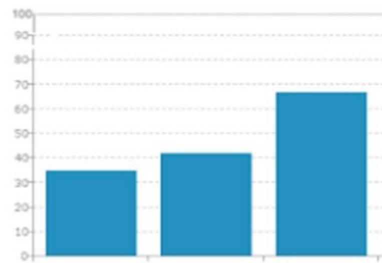
Group 1 scores: (60, 77, 55, 97, 81)
Group 2 scores: (88, 42, 30, 95, 100)

Please put your calculation process here:

Group 1 median: _____________
Group 2 median: _____________

1.5 Which of the following data graph can accurately compare 6 different students' performance between 3 different class assignments? (select one answer but provide reasons for all the options)

◯ Bar chart



Why do you choose/not choose bar chart: ________________

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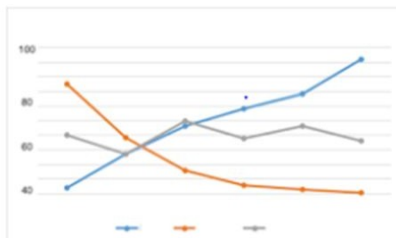
◯ Line chart



Why do you choose/not choose line chart: ________________

____
____
____
____

1.6 Suppose you have four student scores on a math quiz as shown below, will you choose mean or median to better represent the center of these student scores? (select one answer)

Students' math quiz scores: (10, 15, 20, 90)

◯ 1. Mean
◯ 2. Median
◯ 3. I am not sure

Please explain your answer:

2.1 Variance can be generally defined as the average distance of students' scores from their group mean. Given two groups of students' scores below, please write down your calculation process and the variance for group 1 & 2 separately:

Group 1 scores: (60, 82, 78, 70)
Group 2 scores: (42, 68, 58, 82)

Please put your calculation process here:

Group 1 variance: _____________
Group 2 variance: _____________

2.2 For the same two sets of student scores in the previous question, if there is a new score 100 to be added into each group, which of the following is true? (select all that apply)

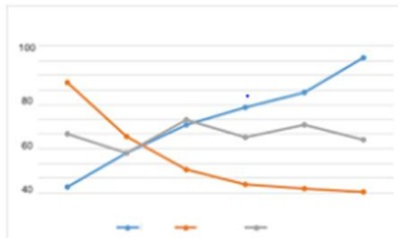
- ☐ 1. The variance will decrease in both group 1 & group 2
- ☐ 2. The variance will increase in both group 1 & group 2
- ☐ 3. The variance will not change in both group 1 & group 2
- ☐ 4. The variance will increase more in group 2 than in group 1
- ☐ 5. The variance will increase more in group 1 than in group 2

2.3 If you have two new student groups, and the variance for group 1 is 78 while the variance for group 2 is 60, how will you interpret students' performance in group 1 and 2 regarding the student performance? (select all that apply)

- ☐ 1. Students' performance in group 1 is more similar to each other than that in group 2
- ☐ 2. Students' performance in group 1 is less similar to each other than that in group 2
- ☐ 3. Students' mean score in group 1 is higher than that in group 2
- ☐ 4. Students' mean score in group 1 is lower than that in group 2

2.4 Which of the following data graph can accurately represent the variance for three different tests at a class level? (select one answer but provide reasons for all options)

◯ Line chart



Why do you choose/not choose line chart: ________________

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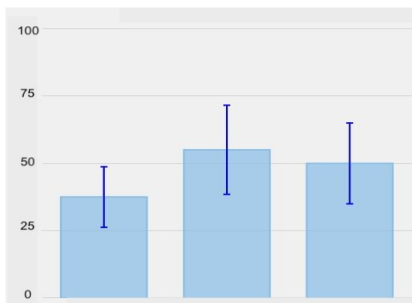
◯ Bar chart



Why do you choose/not choose bar chart: ________________

____

____

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____

2.5 Suppose you have the mean and variance of students' three class quizzes below, how would you compare Class A & B's performance in terms of their mean and variance for each quiz?

	1st quiz	**2nd quiz**	**3rd quiz**
Class A	mean: 85 variance: 80	mean: 60 variance: 180	mean: 90 variance: 35
Class B	mean: 70 variance: 50	mean: 65 variance: 220	mean: 94 variance: 110

Please explain your answer:

3.1 A correlation coefficient (Pearson's r) is a numerical measure of a statistical relationship between two variables ranging from −1 to +1. If you have identified that r = 0.8 between students' quiz 1 & 2 score, and r = 0.2 between quiz 1 & 3, and r= -0.3 between quiz 2 & 3, which of the following is true? (select all that apply)

** assuming all correlation coefficients are statistically significant*

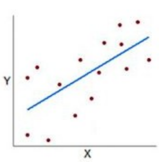
☐ 1. There is a strong negative negative relation between quiz 2 & 3 score
☐ 2. There is a strong positive relation between quiz 1 & 2 score
☐ 3. There is a moderate positive relation between quiz 1, 2, & 3
☐ 4. There is a weak positive relation between quiz 1 & 3 score

Please explain your answer:

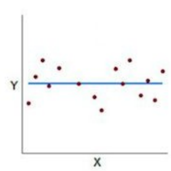
3.2 Please pair each of the following correlation coefficients (Pearson's r) with their corresponding data visualization which best describes the relationship between X and Y

r = +1 : _______ **r = -1 :** _______ **r = +0.7:** ______ **r = - 0.7:** ______ **r = 0:** ______

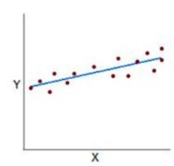
A.



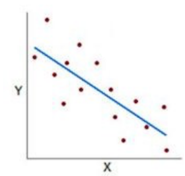
B.



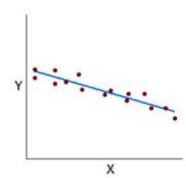
C.



D.



E.



3.3 Given correlation coefficients between scores of 5 different learning activities below, how will you interpret this result? (select all that apply)

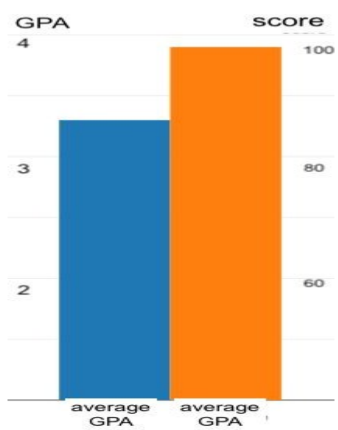
	Quiz 1	Quiz 2	Assignment 1	Assignment 2	Practice Exam	Final Exam
Quiz 1	1.0	0.1	0.7	0.2	0.3	?
Quiz 2	0.1	1.0	0.1	0.8	0.85	?
Assignment 1	0.7	0.1	1.0	0.01	0.04	?
Assignment 2	0.2	0.8	0.01	1.0	0.9	?
Practice Exam	0.3	0.85	0.4	0.9	1.0	?

☐ 1. Students who do well on quiz 1 are likely to do well on quiz 2
☐ 2. Student who do well on assignment 1 are likely to do well on assignment 2
☐ 3. Students who do well on assignment 2 are likely to get high score on the exam
☐ 4. Students who do well on quiz 1 are likely to do assignment 1 well
☐ 5. None of above

Please explain your answer:

3.4 Which of the following graph can inform how students' exam scores correlate with their GPA? (select one answer but provide reasons for all the options)

○ Parallel bar chart



Why do you choose/not choose parallel bar chart:

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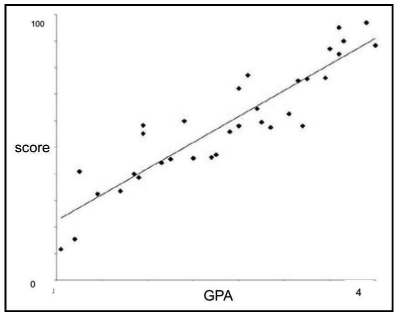
◯Scatterplot



Why do you choose/not choose scatterplot: ________________

____
____
____
____

3.5 Given the same correlation table as in the previous question, what will be some appropriate pedagogical suggestion(s) to make based on the correlation coefficients ? (select all that apply)? (select all that apply)

	Quiz 1	Quiz 2	Assignment 1	Assignment 2	Practice Exam	Final Exam
Quiz 1	1.0	0.1	0.7	0.2	0.3	?
Quiz 2	0.1	1.0	0.1	0.8	0.85	?
Assignment 1	0.7	0.1	1.0	0.01	0.04	?
Assignment 2	0.2	0.8	0.01	1.0	0.9	?
Practice Exam	0.3	0.85	0.4	0.9	1.0	?

☐ 1. The practice exam involves most content knowledge from Quiz 2 and Assignment 2
☐ 2. The practice exam involves most content knowledge from Quiz 1 and Assignment 1
☐ 3. The practice exam involves most content knowledge from Quiz 1 and Quiz 2
☐ 4. The practice exam involves most content knowledge from Assignment 1 and Assignment 2

3.6 If the final exam is going to cover will involve 30% of the content from the two quizzes, and 70% of the content from the two assignments, which learning activities should the teacher focus on to best help the students prepare for the final exam? (circle True or False for each of the questions below)

(1) The teacher should focus on assignment 1 & quiz 1: True False
(2) The teacher should focus on assignment 2 & quiz 2: True False
(3) The teacher should focus on quiz 1 & quiz 2: True False
(4) The teacher should focus on assignment 1 & assignment 2: True False

4.1 Which of the following is the purpose of using regression analysis? (select all that apply)

- ☐ 1. Predicting outcome of output variable based on contribution of input variable(s)
- ☐ 2. Understand the amount of contribution of an input variable to an output variable
- ☐ 3. Identify if the difference between two sets of values is statistically significant
- ☐ 4. Identify the change in output variable given the change in input variable

4.2 Please link each of the following questions with the type function in regression analysis in the following:

1. Does the number of class attendance affect student mid-term exam score?	●	●	**Contribution of one thing to another**
2. What is the relationship between students' quiz score and their test score?	●	●	**Predicting student's score based on an input variable**
3. Is there a significant difference of average math test score between two school classes?	●	●	**Understand the correlation relation between two variables**
4. Give a regression formula: *test score = 15 + 0.85 x homework score* , what is the test score that a student is likely to get if she gets 90 for her homework?	●	●	**Inferential statistical t-test**

4.3 If your goal is to know how each learning activity is likely to contribute to students' final exam score, what is the correct order of steps to take? (choose the correct answers & put the step numbers next to those checked boxes)

- ☐ Run a regression analysis by using learning activities scores to predict the final exam scores
- ☐ Run a correction analysis and observe the relation between different activities scores
- ☐ Check statistical significance, direction, and strength of each coefficient in the regression model
- ☐ Check statistical significance, direction, and strength of each each correlation coefficient
- ☐ Summarize the results

4.4 Please link each of the following statistical terminologies with appropriate explanation below:

1. Variance	●	●	**The probability of obtaining test results at least as extreme as the results actually observed during the test, assuming that the null hypothesis is correct.**
2. Mean	●	●	**A statistical association that refers to the degree to which a pair of variables are linearly related**
3. Correlation	●	●	**The value separating the higher half from the lower half of a data sample. It can be considered as the middle value**
4. P-value	●	●	**The rejection of a true null hypothesis**
5. Median	●	●	**A measure of how far a set of numbers are spread out from their average value**
6. Regression	●	●	**The central value of a discrete set of numbers. The sum of the values divided by the number of values**
7. Type 1 error	●	●	**A statistical processes for estimating the relationships between a dependent variable and one or more independent variables**

5. Please circle only one answer for each of the following questions:

(1) I can assess student performances in the classroom

Disagree 1 2 3 4 5 6 7 Agree

(2) I can adapt my teaching based upon what students currently understand or do not understand

Disagree 1 2 3 4 5 6 7 Agree

(3) I can adapt my teaching style to different learners

Disagree 1 2 3 4 5 6 7 Agree

(4) I can assess student learning in multiple ways

Disagree 1 2 3 4 5 6 7 Agree

(5) I can use a wide range of teaching approaches in a classroom setting

Disagree 1 2 3 4 5 6 7 Agree

(6) I am familiar with common student understandings and misconceptions

Disagree 1 2 3 4 5 6 7 Agree

6. Please circle only one answer for each of the following questions:

(1) Do you feel you can choose technologies that enhance your teaching approaches for a lesson?

Disagree 1 2 3 4 5 6 7 Agree

(2) Do you feel you can choose technologies to enhance students' learning for a lesson?

Disagree 1 2 3 4 5 6 7 Agree

(3) Do you feel you can think critically about how to use technology in your future classroom?

Disagree 1 2 3 4 5 6 7 Agree

(4) Do you feel you can adapt different technologies to different teaching activities?

Disagree 1 2 3 4 5 6 7 Agree

7. Please circle only one answer for each of the following questions:

(1) To what extent can you use a variety of assessment strategies?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(2) To what extent can you provide an alternative explanation or example when students are confused?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(3) To what extent can you craft good questions for your students?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(4) How well can you implement alternative strategies in your classroom?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(5) How much can you do to control disruptive behavior in the classroom?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(6) How much can you do to get children to follow classroom rules?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(7) How much can you do to calm a student who is disruptive or noisy?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(8) How well can you establish a classroom management system with each group of students?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(9) How much can you do to get students to believe they can do well in school?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(10) How much can you do to help your students value learning?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(11) How much can you do to motivate students who show low interest in school?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

(12) How much can you assist families in helping their children do well in school?

Nothing 1 2 3 4 5 6 7 8 9 A great deal

8. Please circle only one answer for each of the following questions:

(1) When I make plans I follow through with them

Disagree	1	2	3	4	5	6	7	Agree

(2) I usually manage one way or another

Disagree	1	2	3	4	5	6	7	Agree

(3) I am able to depend on myself more than anyone else

Disagree	1	2	3	4	5	6	7	Agree

(4) Keeping interested in things is important to me

Disagree	1	2	3	4	5	6	7	Agree

(5) I can be on my own if I have to

Disagree	1	2	3	4	5	6	7	Agree

(6) I feel proud that I have accomplished things in my life

Disagree	1	2	3	4	5	6	7	Agree

(7) I usually take things in stride

Disagree	1	2	3	4	5	6	7	Agree

(8) I am friends with myself

Disagree	1	2	3	4	5	6	7	Agree

(9) I feel that I can handle many things at a time

Disagree	1	2	3	4	5	6	7	Agree

(10) I am determined

Disagree	1	2	3	4	5	6	7	Agree

(11) I seldom wonder what the point of it all is

Disagree	1	2	3	4	5	6	7	Agree

(12) I take things one day at a time

Disagree	1	2	3	4	5	6	7	Agree

(13) I can get through difficult times because I've experienced difficulty before

Disagree 1 2 3 4 5 6 7
Agree

(14) I have self-discipline

Disagree 1 2 3 4 5 6 7
Agree

(15) I keep interest in things

Disagree 1 2 3 4 5 6 7
Agree

(16) I can usually find something to laugh about

Disagree 1 2 3 4 5 6 7
Agree

(17) My belief in myself gets me through hard times

Disagree 1 2 3 4 5 6 7
Agree

(18) In an emergency, I am someone people generally can rely on

Disagree 1 2 3 4 5 6 7
Agree

(19) I can generally look at a situation in a number of ways

Disagree 1 2 3 4 5 6 7
Agree

(20) Sometimes I make myself do things whether I want to or not

Disagree 1 2 3 4 5 6 7
Agree

(21) My life has meaning

Disagree 1 2 3 4 5 6 7
Agree

(22) I do not dwell on things that I can't do anything about

Disagree	1 Agree	2	3	4	5	6	7

(23) When I am in a difficult situation, I can usually find my way out of it

Disagree	1 Agree	2	3	4	5	6	7

(24) I have enough energy to do what I have to do

Disagree	1 Agree	2	3	4	5	6	7

(25) It's okay if there are people who don't like me

Disagree	1 Agree	2	3	4	5	6	7

End of the Survey—Thank you!